Draft Technical Documentation: San Francisco Bay Area UrbanSim Application

prepared for:

Metropolitan Transportation Commission (MTC)

in collaboration with

Association of Bay Area Governments (ABAG)

March 28, 2013

Paul Waddell, Principal Investigator
Urban Analytics Lab
Institute of Urban And Regional Development
University of California, Berkeley

Acknowledgments

The development of OPUS and UrbanSim has been supported by grants from the National Science Foundation Grants CMS-9818378, EIA-0090832, EIA-0121326, IIS-0534094, IIS-0705898, IIS-0964412, and IIS-0964302 and by grants from the U.S. Federal Highway Administration, U.S. Environmental Protection Agency, European Research Council, Maricopa Association of Governments, Puget Sound Regional Council, Oahu Metropolitan Planning Organization, Lane Council of Governments, Southeast Michigan Council of Governments, Metropolitan Transportation Commission and the contributions of many users.

This application of UrbanSim to the San Francisco Bay Area has been funded by the Metropolitan Transportation Commission (MTC).

The UrbanSim Development and Application Team

UrbanSim is an urban simulation system designed by Paul Waddell, and developed over a number of years with the effort of many individuals working towards common aims. See the UrbanSim People page for current and previous contributors, at www.urbansim.org/people.

The following persons participated in the development of the UrbanSim Application to the San Francisco Bay Area:

Paul Waddell, City and Regional Planning, University of California Berkeley (Principal Investigator)
Ian Carlton, City and Regional Planning, University of California Berkeley
Brian Cavagnolo, City and Regional Planning, University of California Berkeley
Regina Clewlow, City and Regional Planning, University of California Berkeley
Federico Fernandez, City and Regional Planning, University of California Berkeley
Fletcher Foti, City and Regional Planning, University of California Berkeley
Conor Henley, City and Regional Planning, University of California Berkeley
Eddie Janowicz, City and Regional Planning, University of California Berkeley
Hyungkyoo Kim, City and Regional Planning, University of California Berkeley
Aksel Olsen, City and Regional Planning, University of California Berkeley
Pedro Peterson, City and Regional Planning, University of California Berkeley
Carlos Vanegas, City and Regional Planning, University of California Berkeley
David Von Stroh, City and Regional Planning, University of California Berkeley
Liming Wang, Institute for Urban and Regional Development, University of California Berkeley
David Weinzimmer, City and Regional Planning, University of California Berkeley

UrbanSim Home Page: **www.urbansim.org**

Collaboration with MTC and ABAG Staff

This project has been done in close collaboration with the staff of the Metropolitan Transportation Commission (MTC) and of the Association of Bay Area Governments (ABAG). In particular, we wish to acknowledge the leadership of Ashley Nguyen, the Project Manager for this effort at MTC before turning these duties over to Carolyn Clevenger, as well as the tireless help of Mike Reilly at ABAG, and David Ory at MTC. Many other staff at MTC and at ABAG have participated in the development of the data, the scenarios and the analysis described in this report.

CONTENTS

CHAPTER

ONE

Introduction and Overview of UrbanSim

1.1 Introduction

1.1.1 Bay Area Model Application Project

The project to develop land use models for the Bay Area was initiated by the Metropolitan Transportation Commission (MTC) in support of Plan Bay Area (the Bay Area's first Sustainable Communities Strategy). The project was motivated by the need to develop regional plans to reduce greenhouse gas emissions in response to state legislation that set targets for such reduction, by considering changes in land use patterns in combination with transportation investments.

UrbanSim is a modeling system developed to support the need for analyzing the potential effects of land use policies and infrastructure investments on the development and character of cities and regions. The system has been developed using the Python programming language and supporting libraries, and is licensed as Open Source software. UrbanSim has been applied in a variety of metropolitan areas in the United States and abroad, including Detroit, Eugene-Springfield, Honolulu, Houston, Paris, Phoenix, Salt Lake City, Seattle, and Zürich. The application of UrbanSim for the Bay Area has been developed by the Urban Analytics Lab at UC Berkeley under contract to MTC.

1.1.2 Intended Uses of the Model System

UrbanSim has been developed to support land use, transportation and environmental planning, with particular attention to the regional transportation planning process. The kinds of tasks for which UrbanSim has been designed include the following:

- Predicting land use information[1] for input to the travel model, for periods of 10 to 40 years into the future, as needed for regional transportation planning.
- Predicting the effects on land use patterns from alternative investments in roads and transit infrastructure, or in alternative transit levels of service, or roadway or transit pricing, over long-term forecasting horizons. Scenarios can be compared using different transportation network assumptions, to evaluate the relative effects on development from a single project or a more wide-reaching change in the transportation system, such as extensive congestion pricing.
- Predicting the effects of changes in land use regulations on land use, including the effects of policies to relax or increase regulatory constraints on development of different types, such as an increase in the allowed Floor Area Ratios (FAR) on specific sites, or allowing mixed-use development in an area previously zoned only for one use.
- Predicting land use development patterns in high-capacity transit corridors.

[1] We use the term *land use* broadly, to refer not only to the use of land, but also to represent the characteristics of real estate development and prices, and the location and types of households and businesses.

- Predicting the effects of environmental policies that impose constraints on development, such as protection of wetlands, floodplains, riparian buffers, steep slopes, or seismically unstable areas.
- Predicting the effects of changes in the macroeconomic structure or growth rates on land use. Periods of more rapid or slower growth, or even decline in some sectors, can lead to changes in the spatial structure of the city, and the model system is designed to analyze these kinds of shifts.
- Predicting the possible effects of changes in demographic structure and composition of the city on land use, and on the spatial patterns of clustering of residents of different social characteristics, such as age, household size and income.
- Examining the potential impacts on land use and transportation of major development projects, whether actual or hypothetical. This could be used to explore the impacts of a corporate relocation, or to compare alternative sites for a major development project.

1.1.3 Assumptions and Limitations of the Model System

UrbanSim is a model system, and models are abstractions, or simplifications, of reality. Only a small subset of the real world is reflected in the model system, as needed to address the kinds of uses outlined above. Like any model, or analytical method, that attempts to examine the potential effects of an action on one or more outcomes, there are limitations to be aware of. Some of the assumptions made in developing the model system also imply limitations for its use. Some of the more important of the assumptions and limitations are:

- *Boundary effects are ignored*. Interactions with adjacent metropolitan areas are ignored.
- *The land use regulations are assumed to be binding constraints on the actions of developers*. This is equivalent to assuming that developers who wish to construct a project that is inconsistent with current land use regulations cannot get a waiver or modification of the regulations in order to accommodate the project. This assumption is more reflective of reality in some places than others, depending on how rigorously enforced land policies are in that location. Clearly there are cities in which developer requests for a variance from existing policies meets with little or no resistance. For the purposes the model system is intended, however, this assumption, and the limitation that it does not completely realistically simulate the way developers influence changes in local land use policies, may be the most appropriate. It allows examination of the effects of policies, under the expectation that they are enforced, which allows more straightforward comparisons of policies to be made.
- *Large scale and microscopic events cannot be accurately predicted*. While this limitation applies to any and every model, not just UrbanSim, it bears repeating since the microscopic level of detail of UrbanSim leads to more temptation to over-invest confidence in the micro-level predictions. Though the model as implemented in the Bay Area predicts the location choices of individual jobs, households, and developers, the intent of the model is to predict patterns rather than discrete individual events. No individual prediction made by the model, such as the development of a specific development project on a single parcel in a particular year 20 years from now, is likely to be correct. But the tendencies for parcels in that area to have patterns or tendencies for development is what the model is intended to represent. Model users should therefore not expect to accurately predict large-scale, idiosyncratic events such as the development of a specific high-rise office building on a specific parcel. It would be advisable to aggregate results, and/or to generate multiple runs to provide a distribution of results. A related implication is that the lower level of sensitivity and appropriate use of the model system needs to be determined by a combination of sensitivity testing, experience from use, and common sense. It would not be likely, for example, that changing traffic signalization on a particular collector street intersection would be a large enough event to cause significant changes in model results.
- *Errors in input data will limit the model to some extent*. Efforts were made to find obvious errors in the data, and to prevent these from affecting the results, but there was not sufficient time or resources to thoroughly address all data problems encountered, including some extreme values, missing values, and inconsistencies within and among data sources. The noise in the input data limits to some extent the accuracy of the model, though the statistical estimation of the parameters should help considerably in developing unbiased parameters even in the

presense of missing data and other data errors. Over a longer period of time, it would be well worth investigating how much difference errors in input data make in model results, and to fine-tune a strategy to invest in data where it makes the most effective use of scarce resources.

- *Behavioral pattenrs are assumed to be relatively stable over time*. One of the most common assumptions in models, and one rarely acknowledged, is that behavioral patterns will not change dramatically over time. Models are estimated using observed data, and the parameters reflect a certain range of conditions observed in the data. If conditions were to change dramatically, such as massive innovation in currently unforeseen fuel technology, it is probably the case that fundamental changes in consumption behavior, such as vehicle ownership and use, would result.

1.2 UrbanSim Overview

1.2.1 Design Objectives and Key Features

UrbanSim is an urban simulation system developed over the past several years to better inform deliberation on public choices with long-term, significant effects (Waddell 2002, Waddell, Ulfarsson, Franklin & Lobb 2007, Waddell, Wang & Liu 2008, Waddell 2011). A key motivation for developing such a model system is that the urban environment is complex enough that it is not feasible to anticipate the effects of alternative courses of action without some form of analysis that could reflect the cause and effect interactions that could have both intended and possibly unintended consequences.

Consider a highway expansion project, for example. Traditional civil engineering training from the mid 20th century suggested that the problem was a relatively simple one: excess demand meant that vehicles were forced to slow down, leading to congestion bottlenecks. The remedy was seen as easing the bottleneck by adding capacity, thus restoring the balance of capacity to demand. Unfortunately, as Downs (2004) has articulately explained, and most of us have directly observed, once capacity is added, it rather quickly gets used up, leading some to conclude that 'you can't build your way out of congestion'. The reason things are not as simple as the older engineering perspective would have predicted is that individuals and organizations adapt to changing circumstances. Once the new capacity is available, initially vehicle speeds do increase, but this drop in the time cost of travel on the highway allows drivers taking other routes to change to this now-faster route, or to change their commute to work from a less-convenient shoulder of the peak time to a mid-peak time, or switching from transit or car-pooling to driving alone, adding demand at the most desired time of the day for travel. Over the longer-term, developers take advantage of the added capacity to build new housing and commercial and office space, households and firms take advantage of the accessibility to move farther out where they can acquire more land and sites are less expensive. In short, the urban transportation system is in a state of dynamic equilibrium, and when you perturb the equilibrium, the system, or more accurately, all the agents in the system, react in ways that tend to restore equilibrium. If there are faster speeds to be found to travel to desired destinations, people will find them.

The highway expansion example illustrates a broader theme: urban systems that include the transportation system, the housing market, the labor market (commuting), and other real estate markets for land, commercial, industrial, warehouse, and office space - are closely interconnected - much like the global financial system. An action taken in one sector ripples through the entire system to varying degrees, depending on how large an intervention it is, and what other interventions are occurring at the same time. This brings us to a second broad theme: interventions are rarely coordinated with each other, and often are conflicting or have a compounding effect that was not intended. This pattern is especially true in metropolitan areas consisting of many local cities and possibly multiple counties - each of which retain control of land use policies over a fraction of the metropolitan area, and none of which have a strong incentive, nor generally the means, to coordinate their actions. It is more often the case that local jurisdictions are taking actions in strategic ways that will enhance their competitive position for attracting tax base-enhancing development and residents. It is also systematically the case that transportation investments are evaluated independently of land use plans and the reactions of the real estate market.

UrbanSim was designed to attempt to reflect the interdependencies in dynamic urban systems, focusing on the real estate market and the transportation system, initially, and on the effects of individual interventions, and combinations of them, on patterns of development, travel demand, and household and firm location. Some goals that have shaped the design of UrbanSim, and some that have emerged through the past several years of seeing it tested in the real world, are the following:

Outcome Goals:

- Enable a wide variety of stakeholders (planners, public agencies, citizens and advocacy groups) to explore the potential consequences of alternative public policies and investments using credible, unbiased analysis.
- Facilitate more effective democratic deliberation on contentious public actions regarding land use, transportation and the environment, informed by the potential consequences of alternative courses of action that include long-term cumulative effects on the environment, and distributional equity considerations.
- Make it easier for communities to achieve a common vision for the future of the community and its broader environment, and to coordinate their actions to produce outcomes that are consistent with this vision.

Implementation Goals for UrbanSim:

- Create an analytical capacity to model the cause and effect interactions within local urban systems that are sufficiently accurate and sensitive to policy interventions to be a credible source for informing deliberations.
- Make the model system credible by avoiding bias in the models though simplifying assumptions that obscure or omit important cause-effect linkages at a level of detail needed to address stakeholder concerns.
- Make the model design behaviorally clear in terms of representing agents, actions, and cause - effect interactions in ways that can be understood by non-technical stakeholders, while making the statistical methods used to implement the model scientifically robust.
- Make the model system open, accessible and transparent, by adopting an Open Source licensing approach and releasing the code and documentation on the web.
- Encourage the development of a collaborative approach to development and extension of the system, both through open source licensing and web access, and by design choices and supporting organizational activities.
- Test the system extensively and repeatedly, and continually improve it by incorporating lessons learned from applications, and from new advances in methods for modeling, statistical analysis, and software development.

The original design of UrbanSim adopted several elements to address these implementation goals, and these have remained foundational in the development of the system over time. These design elements include:

- The representation of individual agents: initially households and firms, and later, persons and jobs.
- The representation of the supply and characteristics of land and of real estate development, at a fine spatial scale: initially a mixture of parcels and zones, later gridcells of user-specified resolution.
- The adoption of a dynamic perspective of time, with the simulation proceeding in annual steps, and the urban system evolving in a path dependent manner.
- The use of real estate markets as a central organizing focus, with consumer choices and supplier choices explicitly represented, as well as the resulting effects on real estate prices. The relationship of agents to real estate tied to specific locations provided a clean accounting of space and its use.
- The use of standard discrete choice models to represent the choices made by households and firms and developers (principally location choices). This has relied principally on the traditional Multinomial Logit (MNL) specification, to date.
- Integration of the urban simulation system with existing transportation model systems, to obtain information used to compute accessibilities and their influence on location choices, and to provide the raw inputs to the travel models.
- The adoption of an Open Source licensing for the software, written originally in Java, and recently reimplemented using the Python language. The system has been updated and released continually on the web since 1998 at www.urbansim.org.

The basic features of the UrbanSim model and software implementation are highlighted in Table 1.1. The model is unique in that it departs from prior operational land use models based on cross-sectional, equilibrium, aggregate approaches to adopt an approach that models individual households, jobs, buildings and parcels (or gridcells), and their changes from one year to the next as a consequence of economic changes, policy interventions, and market interactions .

Table 1.1: Key Features of UrbanSim

Key Features of the UrbanSim Model System	• The model simulates the key decision makers and choices impacting urban development; in particular, the mobility and location choices of households and businesses, and the development choices of developers • The model explicitly accounts for land, structures (houses and commercial buildings), and occupants (households and businesses) • The model simulates urban development as a dynamic process over time and space, as opposed to a cross-sectional or equilibrium approach • The model simulates the land market as the interaction of demand (locational preferences of businesses and households) and supply (existing vacant space, new construction, and redevelopment), with prices adjusting to clear market • The model incorporates governmental policy assumptions explicitly, and evaluates policy impacts by modeling market responses • The model is based on random utility theory and uses logit models for the implementation of key demand components • The model is designed for high levels of spatial and activity disaggregation, with a zonal system identical to travel model zones • The model presently addresses both new development and redevelopment, using parcel-level detail
Key Features of the UrbanSim Software Implementation	• The model and user interface is currently compatible with Windows, Linux, Apple OS X, and other platforms supporting Python • The software is implemented in the Open Platform for Urban Simulation (Opus) • The software is Open Source, using the GPL license • The system is downloadable from the web at www.urbansim.org • The user interface focuses on configuring the model system, managing data, running and evaluating scenarios • The model is implemented using object-oriented programming to maximize software flexibility • The model inputs and results can be displayed using ArcGIS or other GIS software such as PostGIS • Model results are written to binary files, but can be exported to database management systems, text files, or geodatabases

1.2.2 Model System Design

The overall architecture of the UrbanSim model system is depicted in Figures 1.1, 1.2, and 1.3. The specification of UrbanSim model components for the parcel data structure utilized for the MTC project are summarized in Table 1.2 In addition to the parcel-based approach as the unit of spatial analysis, the real estate development model was completely restructured to take advantage of the availability of parcel geography in representing actual development projects.

The components of UrbanSim are models acting on the objects in Figures 1.1, 1.2, and 1.3, simulating the real-world actions of agents acting in the urban system. Developers construct new buildings or redevelop existing ones. Buildings are located on land parcels that have particular characteristics such as value, land use, slope, and other environmental characteristics. Governments set policies that regulate the use of land, through the imposition of land use plans, urban growth boundaries, environmental regulations, or through pricing policies such as development impact fees.

Table 1.2: Specification of UrbanSim Model Components Using Parcel Data Structure

Model	Agent	Dependent Variable	Functional Form
Household Location Choice	Household (New or Moving)	Residential Building With Vacant Unit	Multinomial Logit
Employment Location Choice	Establishment (New or Moving)	Non-residential Building With Vacant Space	Multinomial Logit
Building Location Choice	Building	Parcel (With Vacant Land)	Multinomial Logit
Real Estate Price	Parcel	Price	Multiple Regression

Governments also build infrastructure, including transportation infrastructure, which interacts with the distribution of activities to generate patterns of accessibility at different locations that in turn influence the attractiveness of these sites for different consumers. Households have particular characteristics that may influence their preferences and demands for housing of different types at different locations. Businesses also have preferences that vary by industry and size of business (number of employees) for alternative building types and locations.

The model system contains a large number of components, so in order to make the illustrations clearer, there are three 'views' of the system. In Figure 1.1, the focus is on the flow of information related to jobs. Figure 1.2 provides a household-centric view of the model system. Finally, Figure 1.3 provides a view with a focus on real estate.

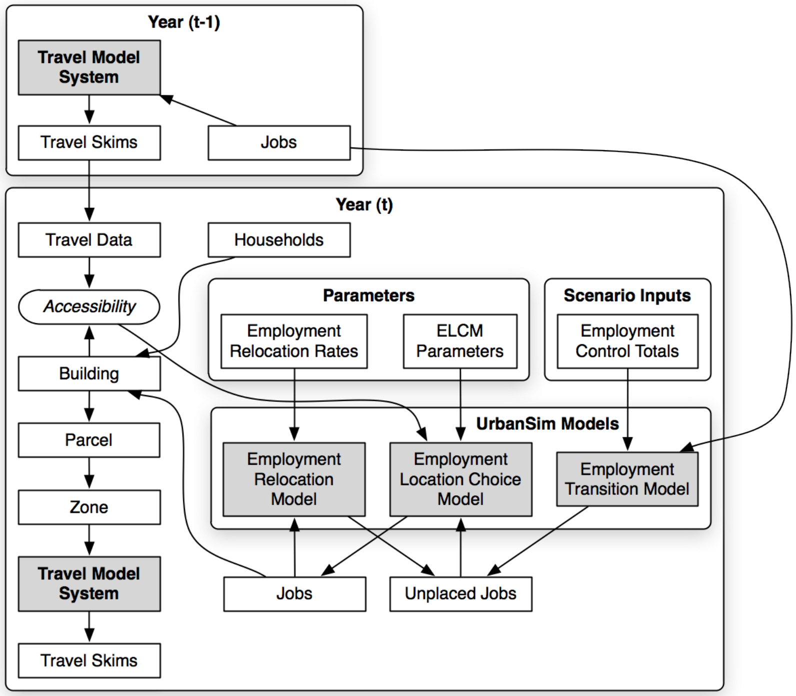


Figure 1.1: UrbanSim Model Flow: Employment Focus

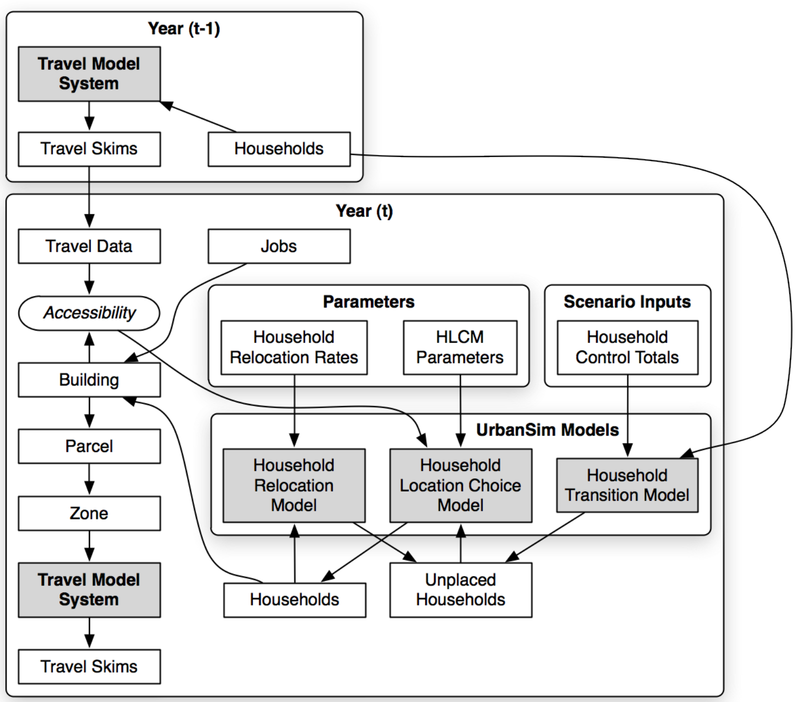


Figure 1.2: UrbanSim Model Flow: Household Focus

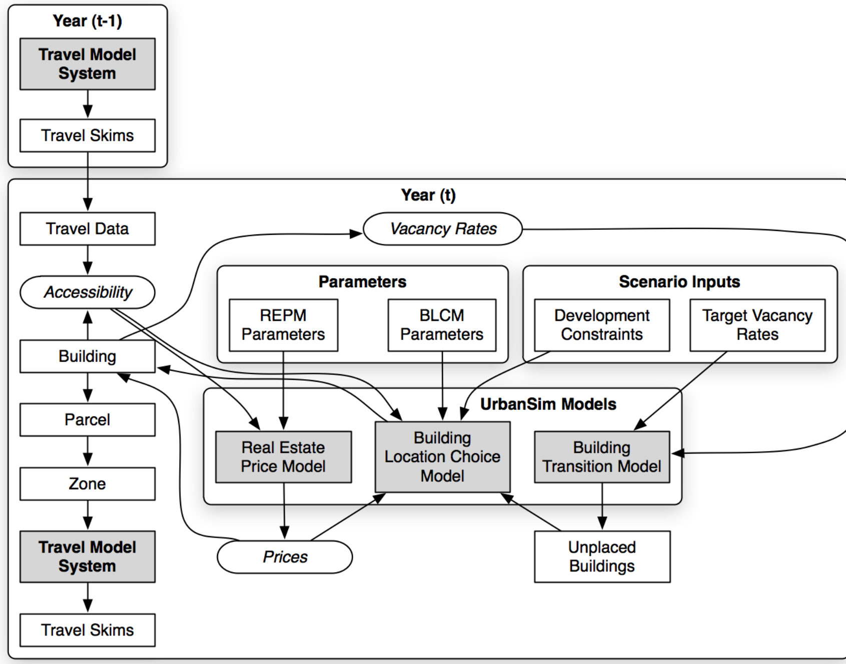


Figure 1.3: UrbanSim Model Flow: Real Estate Focus

UrbanSim predicts the evolution of these entities and their characteristics over time, using annual steps to predict the movement and location choices of businesses and households, the development activities of developers, and the impacts of governmental policies and infrastructure choices. The land use model is interfaced with a metropolitan travel model system to deal with the interactions of land use and transportation. Access to opportunities, such as employment or shopping, are measured by the travel time or cost of accessing these opportunities via all available modes of travel.

The data inputs and outputs for operating the UrbanSim model are shown in Table 1.3. Developing the input database is challenging, owing to its detailed data requirements. A GIS is typically used to manage and combine these data into a form usable by the model, and can also be used to visualize the model results. Fortunately, freely available Open Source GIS tools such as Quantum GIS and PostGIS are now generally sufficiently robust to handle these needs. Once the database is compiled, the model equations must be calibrated and entered into the model. A final step before actual use of the model is a validation process that tests the operation of the model over time and makes adjustments to the dynamic components of the model. The steps of data preparation, model estimation, calibration and validation will be addressed in later chapters. In the balance of this chapter the design and specification of UrbanSim, using a parcel-based approach adapted for use in the Bay Area, is presented in more detail.

1.2.3 Policy Scenarios

UrbanSim is designed to simulate and evaluate the potential effects of multiple scenarios. We use the term scenario in the context of UrbanSim in a very specific way: a scenario is a combination of input data and assumptions to the model system, including macroeconomic assumptions regarding the growth of population and employment in the study area, the configuration of the transportation system assumed to be in place in specific future years, and general plans of local jurisdictions that will regulate the types of development allowed at each location.

In order to facilitate comparative analysis, a model user such as a Metropolitan Planning Organization will generally adopt a specific scenario as a base of comparison or all other scenarios. This base scenario is generally referred to as

Table 1.3: Data Inputs and Outputs of UrbanSim

UrbanSim Inputs	• Employment data, usually in the form of geocoded business establishments, but alternatively from zonal employment by sector • Household data, merged from multiple census sources • Parcel database, with acreage, land use, housing units, non-residential square footage, year built, land value, improvement value, city and county • City and County General Plans and zoning • GIS Overlays for environmental features such as wetlands, floodways, steep slopes, or other sensitive or regulated lands • Traffic Analysis Zones • GIS Overlays for any other planning boundaries • Travel Model outputs • Development Costs
UrbanSim Outputs (by Parcel), Generally Summarized by Zone	• Households by income, age, size, and presence of children • Employment by industry and land use type • Acreage by land use • Dwelling units by type • Square feet of nonresidential space by type • Real estate prices

the 'baseline' scenario, and this is usually based on the adopted or most likely to be adopted regional transportation plan, accompanied by the most likely assumptions regarding economic growth and land use policies.

1.2.4 Discrete Choice Models

UrbanSim makes extensive use of models of individual choice. A pathbreaking approach to modeling individual actions using discrete choice models emerged in the 1970's, with the pioneering work of McFadden on Random Utility Maximization theory (McFadden 1974, McFadden 1981). This approach derives a model of the probability of choosing among a set of available alternatives based on the characteristics of the chooser and the attributes of the alternative, and proportional to the relative utility that the alternatives generate for the chooser. Maximum likelihood and simulated maximum likelihood methods have been developed to estimate the parameters of these choice models from data on revealed or stated preferences, using a wide range of structural specifications (see (Train 2003)). Early application of these models were principally in the transportation field, but also included work on residential location choices (Quigley 1976, Lerman 1977, McFadden 1978), and on residential mobility (Clark & Lierop 1986).

Let us begin with an example of a simple model of households choosing among alternative locations in the housing market, which we index by i. For each agent, we assume that each alternative i has associated with it a utility U_i that can be separated into a systematic part and a random part:

$$U_i = V_i + \epsilon_i, \tag{1.1}$$

where $V_i = \beta \cdot x_i$ is a linear-in-parameters function, β is a vector of k estimable coefficients, x_i is a vector of observed, exogenous, independent alternative-specific variables that may be interacted with the characteristics of the agent making the choice, and ϵ_i is an unobserved random term. Assuming the unobserved term in (1.1) to be distributed with a Gumbel distribution leads to the widely used multinomial logit model (McFadden 1974, McFadden 1981):

$$P_i = \frac{\mathrm{e}^{V_i}}{\sum_j \mathrm{e}^{V_j}}, \tag{1.2}$$

where j is an index over all possible alternatives. The estimable coefficients of (1.2), β, are estimated with the method of maximum likelihood (see for example (Greene 2002)).

The denominator of the equation for the choice model has a particular significance as an evaluation measure. The log of this denominator is called the *logsum*, or composite utility, and it summarizes the utility across all the alternatives. In the context of a choice of mode between origins and destinations, for example, it would summarize the utility (disutility) of travel, considering all the modes connecting the origins and destinations. It has theoretical appeal as an evaluation measure for this reason. In fact, the logsum from the mode choice model can be used as a measure of accessibility.

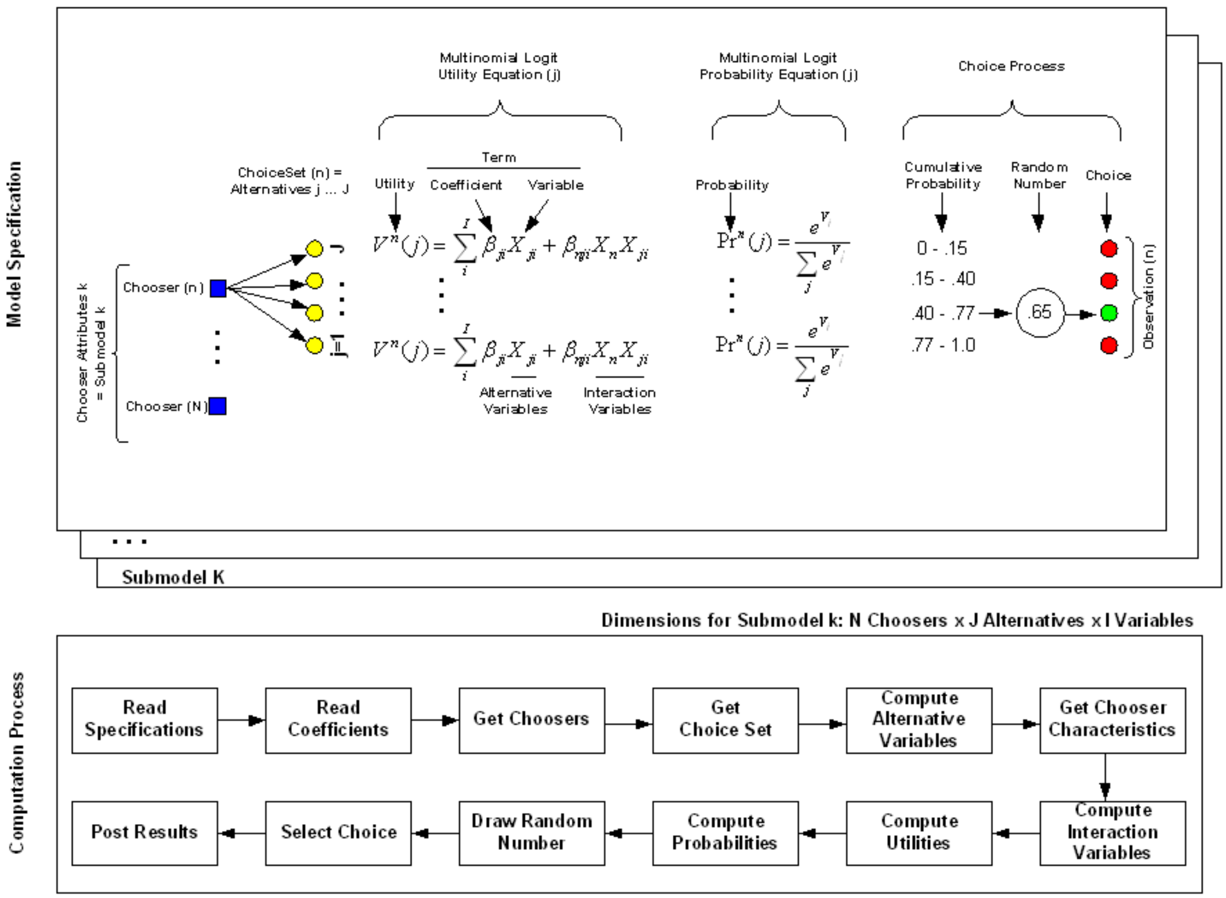


Figure 1.4: Computation Process in UrbanSim Choice Models

Choice models are implemented in UrbanSim in a modular way, to allow flexible specification of models to reflect a wide variety of choice situations. Figure 1.4 shows the process both in the form of the equations to be computed, and from the perspective of the tasks implemented as methods in software.

For each model component within the UrbanSim model system, the choice process proceeds as shown in Figure 1.4. The first steps of the model read the relevant model specifications and data. Then a choice set is constructed for each chooser. Currently this is done using random sampling of alternatives, which has been shown to generate consistent, though not efficient, estimates of model parameters (Ben-Akiva & Lerman 1987).

The choice step in this algorithm warrants further explanation. Choice models predict choice probabilities, not choices. In order to predict choices given the predicted probabilities, we require an algorithm to select a specific choice outcome. A tempting approach would be to select the alternative with the maximum probability, but unfortunatelty this strategy would have the effect of selecting only the dominant outcome, and less frequent alternatives would be completely eliminated. In a mode choice model, for illustration, the transit mode would disappear, since the probability of choosing an auto mode is almost always higher than that of choosing transit. Clearly this is not a desirable or realistic outcome. In order to address this problem, the choice algorithm used for choice models uses a sampling approach. As illustrated in Figure 1.4, a choice outcome can be selected by sampling a random number from the uniform distribution in the range 0 to 1, and comparing this random draw to the cumulative probabilities of the alternatives. Whichever alternative the sampled random number falls within is the alternative that is selected as the 'chosen' one. This algorithm has the property that it preserves in the distribution of choice outcomes a close approximation of the original probability distribution, especially as the sample size of choosers becomes larger.

CHAPTER

TWO

Bay Area UrbanSim Models

This chapter describes each of the models used in the Bay Area application of UrbanSim. The sequence of the presentation of the models is organized approximately in the order of their execution within each simulated year, but in some cases they are grouped for clarity of exposition. All of the models operate as microsimulation models that update the state of individual agents and objects: households, businesses, parcels and buildings. The state of the simulation is updated by each model, and results are stored in annual steps from the base year of 2010 that the model uses as its initial conditions, to the end year of 2040 for each scenario that is simulated.

2.1 Business Transition Model

2.1.1 Objective

The Business Transition Model predicts new establishments being created within or moved to the region by businesses, or the loss of establishments in the region - either through closure of a business or relocation out of the region.

Employment is classified by the user into employment sectors based on aggregations of Standard Industrial Classification (SIC) codes, or more recently, North American Industry Classification (NAICS) codes. Typically sectors are defined based on the local economic structure. Aggregate forecasts of economic activity and sectoral employment are exogenous to UrbanSim, and are used as inputs to the model. The base year UrbanSim employment data for the MTC application were obtained from ABAG. The employment sectors adopted for this application are shown in Table 2.1.

The Business Transition Model integrates exogenous forecasts of aggregate employment by sector with the UrbanSim database by computing the sectoral growth or decline from the preceding year, and either removing establishments from the database in sectors that are declining, or queuing establishments to be placed in the Business Location Choice Model for sectors that experience growth. If the user supplies only total employment control totals, rather than totals by sector, the sectoral distribution is assumed consistent with the current sectoral distribution. In cases of employment loss, the probability that an establishment will be removed is assumed proportional to the spatial distribution of establishments in the sector. The establishments that are removed vacate the space they were occupying, and this space becomes available to the pool of vacant space for other establishments to occupy in the location component of the model. This procedure keeps the accounting of land, structures, and occupants up to date. New establishments are not immediately assigned a location. Instead, new establishments are added to the database and assigned a null location, to be resolved by the Business Location Choice Model.

2.1.2 Algorithm

The model compares the total number of jobs by sector in the establishments table at the beginning of a simulation year, to the total number of jobs by sector specified by the user in the annual employment control totals for that year. If the control total value is higher, the model adds the necessary number of establishments to the establishments table by sampling existing establishments of the same sector and duplicating them until enough jobs have been added. If the control totals indicate a declining job count for a sector then the appropriate number of establishments in the data are selected at random and removed. The role of this model is to keep the number of jobs in the establishments data in the simulation synchronized with aggregate expectations of employment in the region. In most current applications, control totals are separately specified for each sector and split by a proportion that is assumed to be home-based employment vs non-home-based employment. These two are handled by different model groups in the establishment location choice model.

Table 2.1: Employment Sectors

Sector ID	Sector Description
1	Professional services
2	Finance, insurance, and real estate
3	Business services
4	Agriculture
5	Natural resources
6	Arts and recreation
7	Government
8	Other education
9	Logistics
10	Eating and drinking
11	Regional retail
12	Social services
13	Leasing
14	Heavy manufacturing
15	Health
16	Local retail
17	Transportation
18	Higher education
19	Utilities
20	Construction
21	Biotechnology
22	Light manufacturing
23	Information
24	Hotel
25	Tech manufacturing
26	Personal services
27	K-12 education
28	Unclassified

2.1.3 Configuration

The configuration of the Business Transition Model in the parcel model system is summarized in the following table:

Table 2.2: Configuration of Business Transition Model

Element	Setting
Agent	Establishments
Dataset	Establishments
Model Structure	Rule Based

2.1.4 Data

The following tables are used in the Business Transition Model in the parcel version of UrbanSim.

Table 2.3: Data Used by Business Transition Model

Table Name	Brief Description
annual_business_control_totals	Annual aggregate control totals for employment by sector
jobs	jobs (synthesized from ABAG zonal employment by sector)

2.2 Household Transition Model

2.2.1 Objective

The Household Transition Model (HTM) predicts new households migrating into the region, or the loss of households emigrating from the region, or the net increase in households due to individuals leaving an existing household to form a new one.

The Household Transition Model accounts for changes in the distribution of households by type over time, using an algorithm analogous to that used in the Business Transition Model. In reality, these changes result from a complex set of social and demographic changes that include aging, household formation, divorce and household dissolution, mortality, birth of children, migration into and from the region, changes in household size, and changes in income, among others. The data (and theory) required to represent all of these components and their interactions adequately are complex, and although these behaviors have been recently implemented in UrbanSim they were not available for use within the time constraints of this project. In this application, the Household Transition Model, like the Business Transition Model described above, uses external control totals of population and households by type (the latter only if available) to provide a mechanism for the user to approximate the net results of these changes. Analysis by the user of local demographic trends may inform the construction of control totals with distributions of household size, age of head, and income. If only total population is provided in the control totals, the model assumes that the distribution of households by type remains static.

As in the business transition case, newly created households are added to a list of movers that will be located to submarkets by the Household Location Choice Model. Household removals, on the other hand, are accounted for by this model by removing those households from the housing stock, and by properly accounting for the vacancies created by their departure. The household transition model is analogous in form to the business transition model described above. The primary household attributes stored on the household table in the database are shown in Table 2.4. Income and persons are the most commonly used attributes to include in the control totals in order to be able to set household targets for income and household size distribution in future years.

Table 2.4: Household Attributes

Characteristic	Description
Tenure	Rent or Own
Building Type	Single Family Detached, Single Family Duplex, Apartment, Townhouse, Group Quarters
Income	Annual Household Income
Persons	Total Persons in Household
Children	Number of Children (under 18) in Household
Race	Race of Head of Household
Workers	Number or Workers in Household
Vehicles	Number of Vehicles

2.2.2 Algorithm

The model compares the total number of households (by type) in the households table at the beginning of a simulation year, to the total number of households (by type) specified by the user in the annual household control totals for that year. If the control total value is higher, the model adds the necessary number of households to the household table by sampling existing households (of the same type) and duplicating them. If the control totals indicate a declining household count (by type) then the appropriate number of households in the data are selected at random and removed. The role of this model is to keep the household data in the simulation synchronized with aggregate expectations of population and households. Note that the model can be configured by the user's choice of specification of the annual control totals. If no household characteristics are included in the control totals, then the synchronization is done for the total number of households. Otherwise it is done by the categories present in the control totals.

2.2.3 Configuration

The configuration of the HTM in the parcel model system is summarized in the following table:

Table 2.5: Configuration of Household Transition Model

Element	Setting
Agent	Household
Dataset	Household
Model Structure	Rule Based

2.2.4 Data

The following tables are used by the Household Transition Model in the parcel version of UrbanSim.

Table 2.6: Data Used by Household Transition Model

Table Name	Brief Description
annual_household_control_totals	Annual aggregate control totals for households, optionally by type
households	Synthesized households
persons	Synthesized persons

2.3 Business Relocation Model

2.3.1 Objective

The Business Relocation Model predicts the relocation of establishments within the region each simulation year.

Employment relocation and location choices are made by firms. In the current version of UrbanSim, we use establishments as the units of analysis (specific sites/branches of a firm). The Business Relocation Model predicts the probability that establishments of each type will move from their current location or stay during a particular year. Similar to the economic transition model when handling job losses in declining sectors, the model assumes that the probability of moving varies by sector but not spatial characteristics. All placement of establishments is managed through the business location choice model.

As in the case of job losses predicted in the economic transition component, the application of this model requires subtracting jobs by sector from the buildings they currently occupy, and the updating of the accounting to make this space available as vacant space. These counts will be added to the unallocated new jobs by sector calculated in the economic transition model. The combination of new and moving jobs serve as a pool to be located in the employment location choice model. Vacancy of nonresidential space will be updated, making space available for allocation in the employment location choice model.

Since it is possible that the relative attractiveness of commercial space in other locations when compared with an establishment's current location may influence its decision to move, an alternative structure for the mobility model could use the marginal choice in a nested logit model with a conditional choice of location. In this way, the model would use information about the relative utility of alternative locations compared to the utility of the current location in predicting whether jobs will move. While this might be more theoretically appealing than the specification given, it is generally not supported by the data available for calibration. Instead, the mobility decision is treated as an independent choice, and the probabilities estimated by annual mobility rates directly observed over a recent period for each sector.

2.3.2 Algorithm

The Business Relocation Model is implemented as a cross-classification rate-based model, with a probability of moving by employment sector applied to each establishment, each simulation year. For example, if an establishment is in the retail sector, their probability of moving would be looked up by finding the retail sector entry in the annual_business_relocation_rates table. Let's assume the rate in the table is .25. This means there is a 25% chance the job will move in any given year, and 75% chance they will not move in that year. The model uses Monte Carlo Sampling to determine the outcome. It works by drawing a random number (from the uniform distribution, between 0 and 1), and comparing that random draw to the probability of moving for each household. So with our example establishment's probability of 0.75 that they will stay, if we draw a random number with a value higher than 0.75, we will predict that the job will move in that year.

The outcome of the model is implemented as follows. If an establishment is determined to be a mover because the random draw is greater than (1 - their move probability), then they are moved out of their current location. In practical terms, their building_id, which identifies where they are located, is simply reset to a null value. They remain in the jobs table but temporarily have no assignment to a location.

In the current application of the model in the Bay Area, the relocation rates for establishments was assumed to be zero, due to a combination of data limitations and time constraints to calibrate the model with non-zero relocation rates. This makes the location choices of businesses fixed once the establishment is assigned to a location.

2.3.3 Configuration

The configuration of the BRM is summarized in the following table:

Table 2.7: Configuration of Business Relocation Model

Element	Setting
Agent	Establishment
Dataset	Establishment
Model Structure	Cross-classification rate-based Model

2.3.4 Data

The following tables are used in the Business Relocation Choice model:

Table 2.8: Data Used by Employment Relocation Model

Table Name	Brief Description
annual_business_relocation_rates	Annual relocation rates for establishments by sector
establishments	establishments

2.4 Household Relocation Model

2.4.1 Objective

The Household Relocation Model predicts the relocation of households within the region each simulation year.

The Household Relocation Model is similar in form to the Employment Relocation Model described above. The same algorithm is used, but with rates or coefficients applicable to each household type. For households, mobility probabilities are based on the synthetic population from the MTC Travel Model. This reflects differential mobility rates for renters and owners, and households at different life stages.

Application of the Household Relocation Model requires subtracting mover households by type from the housing stock by building, and adding them to the pool of new households by type estimated in the Demographic Transition Model. The combination of new and moving households serves as a population of households to be located by the Household Location Choice Model. Housing vacancy is updated as movers are subtracted, making the housing available for occupation in the household location and housing type choice model.

An alternative approach configuration is to structure this as a choice model, and specify and estimate it using a combination of household and location characteristics. This could be linked with the location choice model, as a nested logit model. This was not possible to implement in this application due to limitations in the available household travel survey, which did not contain information on relocation of households from their previous residence to their current location.

2.4.2 Algorithm

The Household Relocation Model is implemented as a cross-classification rate-based model, with a probability of moving by age and income category applied to each household in the synthetic population, each simulation year. For example, if a household has head of age 31 and an income of 47,500, their probability of moving would be looked up by finding the interval within the age and income classes in the annual_household_relocation_rates table. Let's assume the rate in the table is .25. This means there is a 25% chance the household will move in any given year, and 75% chance they will not move in that year. The model uses Monte Carlo Sampling to determine the outcome. It works by drawing a random number (from the uniform distribution, between 0 and 1), and comparing that random draw to the probability of moving for each household. So with our example household's probability of 0.75 that they will stay, if we draw a random number with a value higher than 0.75, we will predict that the household will move in that year. The outcome of the model is implemented as follows. If a household is determined to be a mover because the random draw is greater than (1 - their move probability), then they are moved out of their current location. In practical terms, their building_id, which identifies where they are located, is simply reset to a null value. They remain in the household table but do not have a location.

2.4.3 Configuration

The configuration of the HRM is summarized in the following table:

Table 2.9: Configuration of Household Relocation Model

Element	Setting
Agent	Household
Dataset	Household
Model Structure	Cross-classification rate-based Model

2.4.4 Data

The following tables are used in this model.

Table 2.10: Data Used by Household Relocation Model

Table Name	Brief Description
annual_household_relocation_rates	Annual relocation rates for households by type
households	Synthesized households

2.5 Household Tenure Choice Model

2.5.1 Objective

The Household Tenure Choice Model predicts whether each household chooses to rent or own a housing unit each simulation year.

2.5.2 Algorithm

The Household Tenure Choice Model is structured as a choice model using a binary logit specification, and uses a combination of household characteristics to predict the relative probability of owning vs renting. A tenure outcome is predicted using Monte Carlo sampling as described previously, comparing a value drawn randomly from a uniform distribution to the probability of owning predicted by the binary logit model in order to assign a tenure status. Once a tenure is assigned, the household is active only in that side of the housing market: if they are determined to be a renter, then in the Household Location Choice Model they only consider rental housing units to locate in. Similarly for owner households, they only look at properties that are available for sale as owner-occupied units.

2.5.3 Configuration

The configuration of the HTCM is summarized in the following table:

Table 2.11: Configuration of Household Tenure Choice Model

Element	Setting
Agent	Household
Dataset	Household
Model Structure	Binary Logit Model

2.5.4 Data

The following tables are used in this model.

Table 2.12: Data Used by Household Tenure Choice Model

Table Name	Brief Description
households	Synthesized households

2.6 Business Location Choice Model

2.6.1 Objective

The Business Location Choice Model predicts the location choices of new or relocating establishments.

In this model, we predict the probability that an establishment that is either new (from the Business Transition Model), or has moved within the region (from the Business Relocation Model), will be located in a particular employment submarket. Submarkets are used as the basic geographic unit of analysis in the current model implementation. Each business has an attribute of space it needs based on the employment within the establishment, and this provides a simple accounting framework for space utilization within submarkets. The number of locations available for an establishment to locate within a submarket will depend mainly on the total square footage of nonresidential floorspace in buildings within the submarket, and on the density of the use of space (square feet per employee).

The model is specified as a multinomial logit model, with separate equations estimated for each employment sector. For both the business location and household location models, we take the stock of available space as fixed in the short run of the intra-year period of the simulation, and assume that locators are price takers. That is, a single locating establishment or household does not have enough market power to influence the transaction price, and must accept the current market price as given. However, *the price is iteratively adjusted to account for market equilibrating tendencies as the aggregated demand across all agents increases in some submarkets and decreases in others.* This topic is described in a later section on market price equilibration.

The variables included in the business location choice model are drawn from the literature in urban economics. We expect that accessibility to population, particularly high-income population, increases bids for retail and service businesses. We also expect that two forms of agglomeration economies influence location choices: localization economies and inter-industry linkages.

Localization economies represent positive externalities associated with locations that have other firms in the same industry nearby. The basis for the attraction may be some combination of a shared skilled labor pool, comparison shopping in the case of retail, co-location at a site with highly desirable characteristics, or other factors that cause the costs of production to decline as greater concentration of businesses in the industry occurs. The classic example of localization economies is Silicon Valley. Inter-industry linkages refer to agglomeration economies associated with location at a site that has greater access to businesses in strategically related, but different, industries. Examples include manufacturers locating near concentrations of suppliers in different industries, or distribution companies locating where they can readily service retail outlets.

One complication in measuring localization economies and inter-industry linkages is determining the relevant distance for agglomeration economies to influence location choices. At one level, agglomeration economies are likely to affect business location choices between states, or between metropolitan areas within a state. Within a single metropolitan area, we are concerned more with agglomeration economies at a scale relevant to the formation of employment centers. The influence of proximity to related employment may be measured using two scales: a regional scale effect using zone-to-zone accessibilities from the travel model, or highly localized accessibilities using queries of the area immediately around the given parcel. Most of the spatial queries used in the model are of the latter type, because the regional accessibility variables tend to be very highly correlated, and because agglomerations are expected to be very localized.

Age of buildings is included in the model to estimate the influence of age depreciation of commercial buildings, with the expectation that businesses prefer newer buildings and discount their bids for older ones. This reflects the deterioration of older buildings, changing architecture, and preferences, as is the case in residential housing. There is the possibility that significant renovation will make the actual year built less relevant, and we would expect that this would dampen the coefficient for age depreciation. We do not at this point attempt to model maintenance and renovation investments and the quality of buildings.

Density, the inverse of lot size, is included in the location choice model. We expect businesses, like households, to reveal different preferences for land based on their production functions and the role of amenities such as green space and parking area. As manufacturing production continues to shift to more horizontal, land-intensive technology, we expect the discounting for density to be relatively high. Retail, with its concentration in shopping strips and malls, still requires substantial surface land for parking, and is likely to discount bids less for density. We expect service firms to discount for density the least, since in the traditional urban economics models of bid-rent, service firms generally outbid other firms for sites with higher accessibility, land cost, and density.

We might expect that certain sectors, particularly retail, show some preference for locations near a major highway, and are willing to bid higher for those locations. Distance to a highway is measured in meters, using grid spatial queries. We also test for the residual influence of the classic monocentric model, measured by travel time to the CBD, after controlling for population access and agglomeration economies. We expect that, for most regions, the CBD accessibility influence will be insignificant or the reverse of that in the traditional monocentric model, after accounting for these other effects.

Estimation of the parameters of the model is based on a geocoded establishment file (matched to the parcel file to link employment by type to land use by type). A sample of geocoded establishments in each sector is used to estimate the coefficients of the location choice model. As with the Household Location Choice Model, the application of the model produces demand by each employment type for building locations.

The independent variables used in the business location choice model can be grouped into the categories of real estate characteristics, regional accessibility, and urban-design scale effects as shown below:

- Real Estate Characteristics
  Prices
  Development type (land use mix, density)
- Regional accessibility
  Access to population
  Travel time to CBD, airport
- Urban design-scale
  Proximity to highway, arterials
- Local agglomeration economies within and between sectors: center formation

2.6.2 Algorithm

Jobs to be located by this model are those that were added by the EmploymentTransitionModel or predicted to move by the EmploymentRelocationModel. The model selects all those jobs with no location, and identifies all available, vacant nonresidential space within the simulation year. Since the choice sets are generally too large, normally random sampling of alternatives is used to construct plausible sized choice sets. It then uses a Multinomial Logit Model structure to generate location choice probabilities across the choice set for each locating job. The location probabilities are used with Monte Carlo Sampling to make a determination for each job regarding which of the available locations they will choose. Once a job has chosen a location, that location is committed to the job (like a lease or purchase contract) and the space becomes unavailable for any other locating jobs, until such time as the occupying job is predicted to move.

In the current application, the Business Location Choice Model is run iteratively with a price adjustment component, to reflect a short-term price equilibration process.

2.6.3 Configuration

The configuration of the BLCM in the parcel model system is summarized in the following table:

Table 2.13: Configuration of Bmployment Location Choice Model

Element	Setting
Agent	Establishment
Location Set	Employment submarkets - which are defined by jurisdiction, building type, and transit proximity.
Dependent Variable	Location of each establishment: employment_submarket_id
Model Type	Multinomial Logit Model
Estimation Method	Maximum Likelihood
Submodels	Sector - separate models are specified for groups of jobs by employment sector
Independent Variables	Attributes of submarkets: Price, density, accessibility, composition of households and employment

2.6.4 Data

The following tables are used by the Business Location Choice Model:

Table 2.14: Data Used by Business Location Choice Model

Table Name	Brief Description
establishment	Establishments table with an inventory of employment
employment_sectors	Employment sectors, defined using NAICS or SIC classifications of industry
buildings	Buildings from which available non-residential sqft are evaluated for location
zones	Zones are used to compute density, social composition, and accessibility variables
travel_data	Skims from the travel model are used to compute accessibility variables

2.7 Household Location Choice Model

2.7.1 Objective

The Household Location Choice Model (HLCM) predicts the location choices of new or relocating renter and owner households.

In this model, as in the employment location model, we predict the probability that a household that is either new (from the transition component), or has decided to move within the region (from the household relocation model) and has determined whether to rent or own a unit (from the household tenure choice model), will choose a particular location defined by a residential submarket. As before, the form of the model is specified as multinomial logit, with random sampling of alternatives from the universe of submarkets with vacant housing.

For both the household location and business location models, we take the stock of available space as fixed in the short run of the intra-year period of the simulation, and assume that locators are price takers. That is, a single locating household does not have enough market power to influence the transaction price (or rent), and must accept the current market price as given. However, *the price (or rent) is iteratively adjusted to account for market equilibrating tendencies as the aggregated demand across all agents increases in some submarkets and decreases in others.* This topic is described in a later section on market price equilibration.

The model architecture allows location choice models to be estimated for households stratified by income level, the presence or absence of children, and other life cycle characteristics. Alternatively, these effects can be included in a single model estimation through interactions of the household characteristics with the characteristics of the alternative locations. The current implementation is based on the latter but is general enough to accommodate stratified estimation, for example by household income.

For the Bay Area application of the model, households are stratified by 4 income categories cross-classified with household size of 1, 2, 3 or more. Income and household size provide a strong basis for differentiating among consumers with substantially different preferences and trade-offs in location choices.

We further differentiate households by their tenure choice, given the importance of this distinction for understanding the impacts of housing prices and rents on location choices. Predictions of tenure for each household are made by the Household Tenure Choice Model, discussed in Section 2.5.

The variables used in the model are drawn from the literature in urban economics, urban geography, and urban sociology. An initial feature of the model specification is the incorporation of the classical urban economic trade-off between transportation and land cost. This has been generalized to account not only for travel time to the classical monocentric center, the CBD, but also to more generalized access to employment opportunities and to shopping. These accessibilities to work and shopping are measured by weighting the opportunities at each destination zone with a composite utility of travel across all modes to the destination, based on the logsum from the mode choice travel model.

These measures of accessibility should negate the traditional pull of the CBD, and, for some population segments, potentially reverse it. In addition to these accessibility variables, we include in the model a net building density, to measure the input-substitution effect of land and capital. To the extent that land near high accessibility locations is bid up in price, we should expect that builders will substitute capital for land and build at higher densities. Consumers for whom land is a more important amenity will choose larger lot housing with less accessibility, and the converse should hold for households that value accessibility more than land, such as higher income childless households.

The age of housing is considered for two reasons. First, we should expect that housing depreciates with age, since the expected life of a building is finite, and a consistent stream of maintenance investments are required to slow the deterioration of the structure once it is built. Second, due to changing architectural styles, amenities, and tastes, we should expect that the wealthiest households prefer newer housing, all else being equal. The exception to this pattern is likely to be older, architecturally interesting, high quality housing in historically wealthy neighborhoods. The preference for these alternatives are accommodated through a combination of nonlinear or dummy variable treatment for this type of housing and neighborhood.

A related hypothesis from urban economics is that, since housing is considered a normal good, it has a positive income elasticity of demand. This implies that as incomes rise, households will spend a portion of the gains in income to purchase housing that is more expensive, and that provides more amenities (structural and neighborhood) than their prior dwelling. A similar hypothesis is articulated in urban sociology in which upward social mobility is associated with spatial proximity to higher status households. Both of these hypotheses predict that households of any given income level prefer, all else being equal, to locate in neighborhoods that have higher average incomes. (UrbanSim does not attempt to operationalize the concepts of social status or social assimilation, but does consider income in the location choice.)

The age hypothesis and the two income-related hypotheses are consistent with the housing filtering model, which explains the dynamic of new housing construction for wealthy households that sets in motion a chain of vacancies. The vacancy chain causes households to move into higher status neighborhoods than the ones they leave, and housing units to be successively occupied by lower and lower status occupants. At the end of the vacancy chain, in the least desirable housing stock and the least desirable neighborhoods, there can be insufficient demand to sustain the housing stock and vacancies go unsatisfied, leading ultimately to housing abandonment. We include in the model an age depreciation variable, along with a neighborhood income composition set of variables, to collectively test the housing filtering and related hypotheses.

One of the features that households prefer is a compatible land use mix within the neighborhood. It is likely that residential land use, as a proxy for land uses that are compatible with residential use, positively influences housing bids. On the other hand, industrial land use, as a proxy for less desirable land use characteristics, would lower bids.

The model parameters are estimated using a random sample of alternative locations, which has been shown to provide consistent estimates of the coefficients. In application for forecasting, each locating household is modeled individually, and a sample of alternative cell locations is generated in proportion to the available (vacant) housing. Monte carlo simulation is used to select the specific alternative to be assigned to the household, and vacant and occupied housing units are updated in the cell.

The independent variables can be organized into the three categories of housing characteristics, regional accessibility, and urban-design scale effects as shown below.

- Housing Characteristics
  Prices (interacted with income)
  Development types (density, land use mix) Housing age
- Regional accessibility
  Job accessibility by auto-ownership group
  Travel time to CBD and airport
- Urban design-scale (local accessibility)
  Neighborhood land use mix and density
  Neighborhood Employment

2.7.2 Algorithm

Households to be located by this model are those that were added by the HouseholdTransitionModel or predicted to move by the HouseholdRelocationModel. The model selects all those households of a specified tenure status (renter or owner) that need to find a housing unit, and identifies all available, vacant housing units within the simulation year that are of the appropriate tenure. Since the choice sets are generally too large, normally random sampling of alternatives is used to construct plausible sized choice sets. It then uses a Multinomial Logit Model structure to generate location choice probabilities across the choice set for each household. The location probabilities are used with Monte Carlo Sampling to make a determination for each household regarding which of the available locations they will choose. Once a household has chosen a location, that location is committed to the household (like a rental contract or closing on a purchase of a house) and the residential unit becomes unavailable for any other households, until such time as the occupying household is predicted to move.

2.7.3 Configuration

The configuration of the Household Location Choice Model is summarized in the following table:

Table 2.15: Configuration of Household Location Choice Model

Element	Setting
Agent	Job
Location Set	Residential submarkets - which are defined by building type, school district, tenure, and transit proximity
Dependent Variable	Location of each household: submarket_id
Model Type	Multinomial Logit Model
Estimation Method	Maximum Likelihood
Submodels	Separate models can be specified for groups of households
Independent Variables	Attributes of households interacted with attributes of submarkets

2.7.4 Data

The following tables are used by the Household Location Choice Model.

Table 2.16: Data Used by Household Location Choice Model

Table Name	Brief Description
households	Synthetic households table
buildings	Buildings from which available residential units are evaluated for location
zones	Zones are used to compute density, social composition, and accessibility variables
travel_data	Skims from the travel model are used to compute accessibility variables

2.8 Real Estate Price Model

2.8.1 Objective

The Real Estate Price Model (REPM) predicts the price per unit of each building. For residential units, the sale price is estimated for owner units, and the rent is estimated for rental units.

UrbanSim uses real estate prices as the indicator of the match between demand and supply of land at different locations and with different land use types, and of the relative market valuations for attributes of housing, nonresidential space, and location. This role is important to the rationing of land and buildings to consumers based on preferences and ability to pay, as a reflection of the operation of actual real estate markets. Since prices enter the location choice utility functions for jobs and households, an adjustment in prices will alter location preferences. All else being equal, this will in turn cause higher price alternatives to become more likely to be chosen by occupants who have lower price elasticity of demand. Similarly, any adjustment in land prices alters the preferences of developers to build new construction by type of space, and the density of the construction.

We make the following assumptions:

1. Households, businesses, and developers are all price-takers individually, and market adjustments are made by the market in response to aggregate demand and supply relationships.
2. Location preferences and demand-supply imbalances are capitalized into land values. Building value reflects building replacement costs only, and can include variations in development costs due to terrain, environmental constraints or development policy.

Following on these assumptions and the best available theory regarding real estate price formation, we begin with a reduced-form hedonic regression model to establish the initial price and rent estimates based on stuctural and locational attributes, and combine this with a second step that incorporates short-term (within a year) market equilbrating tendencies.

2.8.2 Hedonic Price Regression

Real estate prices are modeled using a hedonic regression of the log-transformed property value per square foot on attributes of the parcel and its environment, including land use mix, density of development, proximity of highways and other infrastructure, land use plan or zoning constraints, and neighborhood effects. The hedonic regression may be estimated from sales transactions if there are sufficient transactions on all property types, and if there is sufficient information on the lot and its location. An alternative is to use tax assessor records on land values, which are part of the database typically assembled to implement the model. Although assessor records may contain biases in their assessment, they do provide virtually complete coverage of the land (with notable exceptions and gaps for exempt or publicly owned property).

The hedonic regression equation encapsulates interactions between market demand and supply, revealing an envelope of implicit valuations for location and structural characteristics (DiPasquale & Wheaton 1996). Prices are updated by UrbanSim annually, after all construction and market activity is completed. These end of year prices are then used as the values of reference for market activities in the subsequent year.

The independent variables influencing land prices can be organized into site characteristics, regional accessibility, and urban-design scale effects, as shown below:

- Site characteristics
  Development type
  Land use plan
  Environmental constraints
- Regional accessibility
  Access to population and employment
- Urban design-scale
  Land use mix and density
  Proximity to highway and arterials

Algorithm

The Real Estate Price Model uses a hedonic regression structure, which is a multiple regression, estimated using Ordinary Least Squares (OLS), normally with the price specified as a log of price.

Configuration

The configuration of the REPM in the parcel model system is summarized in the following table:

Table 2.17: Configuration of Real Estate Price Model

Element	Setting
Dataset	Buildings
Dependent Variable	Log of Price Per Unit (per housing unit for residential, per square foot for non-residential buildings)
Model Type	Regression
Submodels	Separate models are specified for each type of building
Independent Variables	Constant, and attributes of building: density, accessibility, zonal composition of households and employment

Data

These tables are used by the Real Estate Price Model:

Table 2.18: Data Used by Real Estate Price Model

Table Name	Brief Description
buildings	Individual buildings located on parcels (can be many per parcel)
residential_units	Individual residential units located within a building
zones	Zones used in the travel model, for accessibility and density variables
travel_data	Zone-to-zone skims from the travel model, for accessibility variables
households	Household data, for socioeconomic and density variables
jobs	Employment data, for accessibility and density variables

2.8.3 Market Price Equilibration

In order to reflect the role of equilibrating tendencies in the market, we have introduced to the Bay Are model application a dampened price equilibration algorithm first described in (Wang & Waddell 2013). The market price equilibration algorithm we use reflects the impact of aggregated individual demands at each submarket on prices, and the resulting effects of the altered prices on individual choice probabilities, inducing a circular causality which requires a fixed point algorithm in order to solve for the market clearing prices. Below is the algorithm for computing the full market price clearing array of prices and demands for each submarket, which we then dampen to reflect partial adjustment towards equilibrium, in recognition of real-world frictional factors that prevent full equilibration within one time period. The dampening factor used for this model application was calibrated to 0.2, meaning that prices adjust one-fifth of the way towards full equilibrium within one year.

We assume a random utility maximization framework as the basis of the residence choices. Let the probability that household (business) n chooses location i from the set C of available residence (business) locations be given by the following multinomial logit form:

$$P_{ni} = Pr(U_{ni} \geq U_{nj}, \forall j \in C) = \frac{e^{V_{ni}}}{\sum_{j \in C} e^{V_{nj}}} \tag{2.1}$$

We further assume price in V_{ni} will be adjusted so that the discrepancy between the supply and aggregated demand by submarket is minimized:

$$\arg\min_{price} \sum\nolimits_i (S_i - D_i)^2, subject\,to\,price \in (Lower\ Bound, Upper\ Bound), \tag{2.2}$$

where S_i is the total supply in submarket i, while D_i the aggregated demand for submarket i. With demand given by equation (2.1), we have

$$D_i = \sum_n P_{ni} = \sum_n \frac{e^{V_{ni}}}{\sum_{j \in C} e^{V_{nj}}} \; i = 1, ..., I \tag{2.3}$$

When V_{ni} is linear in price $V_{ni} = X_{ni}\beta$, it can be proved that the first order derivative with respect to price, i.e. the gradient function, of equation (2.2), is:

$$G = 2(S - D) \begin{bmatrix} M_{11} & M_{1i} & M_{1I} \\ : & M_{ii} & : \\ M_{I1} & ... & M_{II} \end{bmatrix} \tag{2.4}$$

where

$M_{ii} = \sum_n (\beta_{price} P_{ni}(1 - P_{ni}))$,

$M_{ij} = \sum_n (-\beta_{price} P_{ni} P_{nj})$,

S is a 1 x I vector of supply, and

D is a 1 x I vector of aggregated demand,

with β_{price} being the coefficients for the price variable in V. Note that β_{price} does not have to be the same for all n, that is, households can have heterogeneous preference for price.

2.9 Real Estate Developer Model

2.9.1 Objective

The Real Estate Developer Model simulates the location, type and density of real estate development, conversion and re-development events at the level of specific parcels. The design draws partly on the parcel-level real estate development model created for the Puget Sound, which generates development proposals based on pre-defined templates. It generalizes the concept of templates to allow the developer model to configure multiple parameters of development projects in order to maximize profitability of development outcomes, subject to local physical, regulatory and market contexts.

2.9.2 Algorithm

This model is a process for evaluating a proforma for each building type allowed by zoning which should indicate the profitability of a development given a set of inputs which specify the context described above.

The proforma can be conceptualized as a spreadsheet implemented in Python code which performs cash flow analysis with standard financial discounting of cash flows. In this case, the developer model optimizes the building form so that it creates the building type and size which result in the greatest profitability (NPV) for each parcel.

The term developer model usually refers to this "outer loop" which optimizes the building form while the "pro forma" actually computes profitability based on cash flows given a specific set of inputs.

The code for the developer model is found in *urbansim_parcel/proposal*. *developer_model.py* is the controlling function for this module - *bform.py* stores the building form currently used, *profroma.py* does the cash flow accounting, and *devmdl_optimize.py* performs the optimization.

Below is the complete set of inputs - the first section is the set of modeled inputs (i.e. output from another model) and the second section are exogenous inputs which are basic attributes of the parcel. The output of the model is simple: a single net present value and the building type and size of the building which results in the specified optimized NPV.

For this application, the developer model runs each simulated year on all empty parcels, on all parcels within a PDA, on parcels within 800m of Caltrain and BART, and a sampled portion of the other parcels to capture redeveloperment of parcels.

For redevelopment, demolition cost is computed through one of the following: the value of residential owner housing, a simple multiplier for residential rental housing, the price estimated for nonresidential sqft, and a land price based on the value of nearby building prices.

Policies enter the developer model by the zoning (primarily by allowed FAR and building types), and also with a parcel subsidy/fee that is specified for each parcel.

2.9.3 Data

Table 2.19: Data Used by Real Estate Developer Model

Variable Name	Brief Description
PRICES	
single family	Price estimate for single-family housing
multi family	Price estimate for multi-family housing
rent single family	Rent estimate for single-family housing
rent multi family	Rent estimate for multi-family housing
office	Rent estimate for the office building type
retail	Rent estimate for the retail building type
industrial	Rent estimate for the industrial building type
ABSORPTION	
sales absorption	The absorption rate for sales units by building type
sales vacancy	The vacancy rate for sales units by building type
rent absorption	The absorption rate for rental units by building type
rent vacancy rates	The vacancy rate for rental units by building type
SIZES	
average lot size	Typical lot size in the zone for this parcel
sf unit size	Typical single-family unit size in the zone for this parcel
mf unit size	Typical multi-family unit size in the zone for this parcel
ZONING	
building types	Allowable building types for this parcel
FAR	Floor area ratio allowed for this parcel
height	Height limits for this parcel
max_dua	Max dwelling units for this parcel
POLICIES	
Regional development fee	Whether to apply indirect source rule. Regional development fees are user-specified
unit subsidy	User-specified per-unit subsidies
per sqft subsidy	User-specified per-unit subsidies for non-residential square feet

2.10 Government and Schools Allocation

2.10.1 Objective

Government and public education jobs are not typically a part of the market-based economy, and the allocation of these jobs does not occur in the same way as other market-based jobs. Since these jobs are more closely tied to the geographic distribution of the population and the locations of existing government and education jobs, a different model was developed for allocating jobs in the government and public education sectors. The basis of the government and education jobs allocation was that local government jobs and local schools jobs would grow along with the local population. There would be potential for new locations for schools and local government facilities within the community, but with more of the jobs expected at existing locations. For county, state, federal and higher education jobs, on the other hand, would grow with the county and regional population, and only in locations of existing government and education jobs and at roughly the same proportions.

2.10.2 Algorithm

To allocate future government and education jobs, coefficients were developed for each TAZ to represent rates of jobs per population. The coefficients were developed in a multi-step process.

Three classes of jobs were identified in the government and public education sectors:

1. Jobs based on the local city-level population; these jobs include jobs with local government agencies and jobs with local public primary and secondary schools.
2. Jobs based on the county-level population; these jobs include county government and special district jobs.
3. Jobs based on the regional-level population; these include state and federal government jobs, and jobs at public institutions of higher education.

Each of the government establishments in the NETS dataset was then coded as local, county, or regional. Similarly, each of the public education establishments were coded as local or regional.

For local jobs, using the 2010 Census population totals by city and the NETS job distribution, rates of government and education employees were calculated for each city by city jobs by city 2010 population. The coefficient for each TAZ is calculated by the following equation:

$$c = Jobs_{2010} + PopGrowth * RateCity * Pop_{2040} \tag{2.5}$$

where

c is the TAZ coefficient for local government jobs or local education jobs. For the local education jobs, c cannot exceed the twice the citywide jobs per population rate; for the local government jobs coefficient, c cannot exceed 5 times the city wide jobs per population rate.

$Jobs_{2010}$ is the total local jobs in the TAZ - local government or education, depending on the coefficient.

$PopGrowth$ is the estimated population growth in the TAZ.

$RateCity$ is 2010 city jobs divided by the 2010 city population.

Pop_{2040} = the estimated 2040 population in the TAZ.

The calculation of the coefficients for the county - and regional-based jobs is more straight forward. For county jobs, the coefficient was calculated by dividing the total county jobs in the TAZ by the county population. Separate coefficients were developed for state, federal and higher education jobs, but each was calculated in the same manner. The coefficient for each TAZ equals the total 2010 jobs divided by total 2010 regional population.

The result is a set of 6 coefficients for each TAZ: for local education jobs, local government jobs, county government jobs, state government jobs, federal government jobs (includes other regionally-based jobs), and for higher education jobs. Each coefficient is applied to the total TAZ population to derive the TAZ-level government and education jobs by type. The final step is to rebalance the totals proportionally to meet regional control totals.

2.11 The Role of Accessibility

Accessibility is a very important influence in urban space, and it similarly plays an important role in UrbanSim. Almost all models in UrbanSim consider the effects of accessibility. But unlike the monocentric or spatial interaction models, in which the choice of workplace is exogenous and residential locations are chosen principally on the basis of commute to the city center or to a predetermined workplace, we deal with accessibility in a more general framework. Accessibility is considered a normal good, like other positive attributes of housing, which consumers place a positive economic value on. We therefore expect that consumers value access to workplaces and shopping opportunities, among the many other attributes they consider in their housing preferences. However, not all households respond to accessibility in the same way. Retired persons would be less influenced by accessibility to job opportunities than would working age households, for instance.

We operationalize the concept of accessibility for a given location as the distribution of opportunities weighted by the travel impedance, or alternatively the utility of travel to those destinations. A number of alternative accessibility measures have been developed in UrbanSim.

The accessibility model reads the auto and transit accessibility measures from the travel model, as well as the land use distribution for a given year, and creates accessibility indices for use in the household and business location choice models. The general framework is to summarize the accessibility from each zone to various activities for which accessibility is considered important in household or business location choice.

Since UrbanSim operates annually, but travel model updates are likely to be executed for two to three of the years within the forecasting horizon, travel utilities remain constant from one travel model run until they are replaced by the next travel model result.

2.12 User-Specified Events

Given our current understanding, no model will be able to simulate accurately the timing, location and nature of major events such as a major corporate relocation into or out of a metropolitan area, or a major development project such as a regional shopping mall. In addition, major policy events, such as a change in the land use plan or in an Urban Growth Boundary, are outside the range of predictions of our simulation. (At least in its current form, UrbanSim is intended as a tool to aid planning and civic deliberation, not as a tool to model the behavior of voters or governments. We want it to be used to say “if you adopt the following policy, here are the likely consequences," but not to say “UrbanSim predicts that in 5 years the county will adopt the following policy.")

However, planners and decision-makers often have information about precisely these kinds of major events, and there is a need to integrate such information into the use of the model system. It is useful, for example, to explore the potential effects of a planned corporate relocation by introducing user-specified events to reflect the construction of the corporate building, and the relocation into the region (and to the specific site) of a substantial number of jobs, and examine the cumulative or secondary effects of the relocation on further residential and employment location and real estate development choices. Inability to represent such events, in the presence of knowledge about developments that may be ‘in the pipeline,’ amounts to less than full use of the available information about the future, and could undermine the validity and credibility of the planning process. For these reasons, support for three kinds of events has been incorporated into the system: development events, employment events, and policy events.

CHAPTER

THREE

Model Data Structures

This chapter describes the Bay Area UrbanSim base-year database. The data structure of each table is described, data sources and processing steps are noted, and selected variables are profiled or mapped to illustrate trends and assess reasonableness. The status of each table in terms of completeness and conformance to UrbanSim schema requirements is also noted.

The year 2010 was selected as the base year for the parcel-based model system. The Bay Area UrbanSim application operates at the level of individual households, jobs, buildings, and parcels. The area defined for the Bay Area model application, which determined the geographic extent of the data collection effort, encompasses the 9-county Bay Area.

Each of the tables is discussed in turn. In some cases, missing data were imputed. Together, the tables represent the distribution of employment, population, and buildings in the Bay Area. Establishments and households are linked to specific buildings, and buildings are linked to parcels. The base-year database contains 2,616,085 households (not including group quarters), 3,385,281 jobs, 1,936,261 buildings, and 2,023,878 parcels.

3.1 annual_business_control_totals

The annual_business_control_totals table contains aggregate targets for number of jobs by sector and year. The table is used by the Business Transition Model, which adds or subtracts establishments to match the job targets. These exogenous employment control totals are a key driver of the simulation.

Column Name	Data Type	Description
year	integer	
sector_id	integer	Index into the `sectors` table
total_number_of_jobs	integer	Target employment for this sector and year

A Bay Area-specific annual_employment_control_totals table has been prepared and formatted for use in UrbanSim. The unique identifiers are "year" and "sector_id". The 28 referenced sector_id's are those shown in the sectors table. The only sector not represented in this table is Military. For each sector, employment totals are given for each year in 2010-2040.

The data source of this table is economic projections for the Bay Area provided by the Association of Bay Area Governments (ABAG). ABAG employment projections are provided for 28 sectors for the years 2011, 2015, 2018, 2020, 2025, 2035, and 2040. Projections were interpolated to provide estimates of the years in between.

The annual_employment_control_totals table shows a 28.4% growth in total employment between 2010 and 2035. Two sectors are projected to experience a decline in total employment: agriculture and natural resources. The three fastest growing sectors are: professional services, business services, and unclassified. Figure 3.1 shows total employment growth.

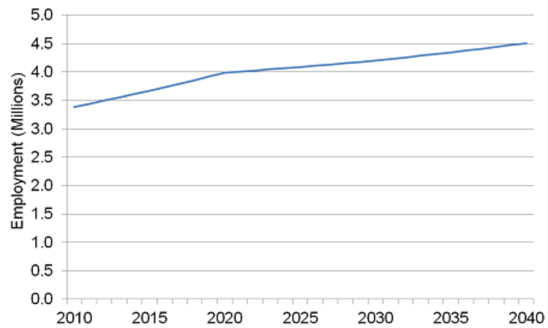


Figure 3.1: Employment Controls- Total Employment, 2010-2040

3.2 annual_household_control_totals

The annual_household_control_totals table represents aggregate targets for number of households by type and year. It is used by the Household Transition Model. These exogenous household control totals are a key driver of the simulation.

Column Name	Data Type	Description
year	integer	
income_1989_category	integer	Income category (in 1989 USD)
total_number_of_households	integer	Target quantity of households for this year and household size category

A Bay Area-specific annual_household_control_totals table has been prepared and formatted for use in UrbanSim. For each year 2010-2040, this table gives target quantities of households by household size. The unique identifiers are "year" and "income_1989_category".

The data source of this table is ABAG's demographic projections for the Bay Area, which are provided for the years 2011, 2015, 2018, 2020, 2025, 2030, 2035, and 2040. The group quarters population, which has remained relatively constant, is not included in the control totals.

The annual_household_control_totals table shows a 22.2% growth in total households between 2010 and 2035. Figure 3.2 shows total household growth; the total number of households grows between 2010 and 2035.

3.3 annual_household_relocation_rates

The annual_household_relocation_rates table contains, for each household type, the probability of moving within the region in a given year. It is used by the Household Relocation Model. A Bay Area-specific annual_household_relocation_rates table has been prepared and formatted for UrbanSim. The Bay Area table breaks down the probabilities by household income, and age of head categories. The rates are assumed to stay constant from year to year.

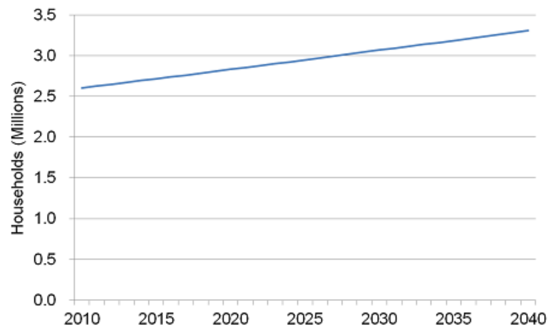


Figure 3.2: Household Controls- Total Households, 2010-2040

Column Name	Data Type	Description
age_of_head_min	integer	The minimum age for which this probability is valid.
age_of_head_max	integer	The maximum age for which this probability is valid, -1 means no maximum
income_min	integer	The minimum income for which this probability is valid.
income_max	integer	The maximum income for which this probability is valid, -1 means no maximum
probability_of_relocating	float	The probability of household relocating in a year.

The ACS PUMS was used to develop the Bay Area's household relocation rates by 6 age-of-head, and 4 income categories (weighted rates). Age of head and income categories were cross-classified to definitions that showed the expected variation across different cutoff levels. In general, the probability of a household relocating decreases with age of the householder.

3.4 annual_business_relocation_rates

The annual_business_relocation_rates table contains probabilities that establishments by sector will relocate within the region within a one-year time frame. It is used by the Business Relocation Model.

Column Name	Data Type	Description
sector_id	integer	Index into the `employment_sectors` table
business_relocation_probability	float	Probability that a business in this sector will relocate within the time span of one year

3.5 buildings

This table contains individual buildings located on a parcel. There can be multiple buildings on a parcel (a many to one relationship between buildings and parcels), and each building links to a specific parcel id. Each household and establishment (or business) is assigned to a specific building. The buildings table is modified by the real estate development and price models. Buildings represent the alternative locations that households and businesses choose amongst in the Household Location Choice Model and Business Location Choice Model.

Column Name	Data Type	Description
building_id	integer	Unique identifier for the building
building_type_id	integer	Identifier for building type
year_built	integer	Year of building construction
building_sqft	integer	Number of square feet in the building
hline non_residential_sqft	integer	Non-residential square footage of building
stories	integer	Number of stories in the building
residential_units	integer	Number of residential units in the building
non_residential_rent	integer	Non-residential rent
tenure	integer	rent (1) vs. own (2)
imputed	integer	Missing data imputed: yes (1) vs. no (0)
parcel_id	integer	Identifier of parcel in which building is located

The building table was derived from parcel data received from ABAG. The location identifier is the parcel_id. The building type identifier, building_type, refers to the ABAG building typology in the building_type table.

The base-year buildings table contains 1,936,261 building records. Figures 3.3 through 3.8 map out various building attributes at the zonal level.

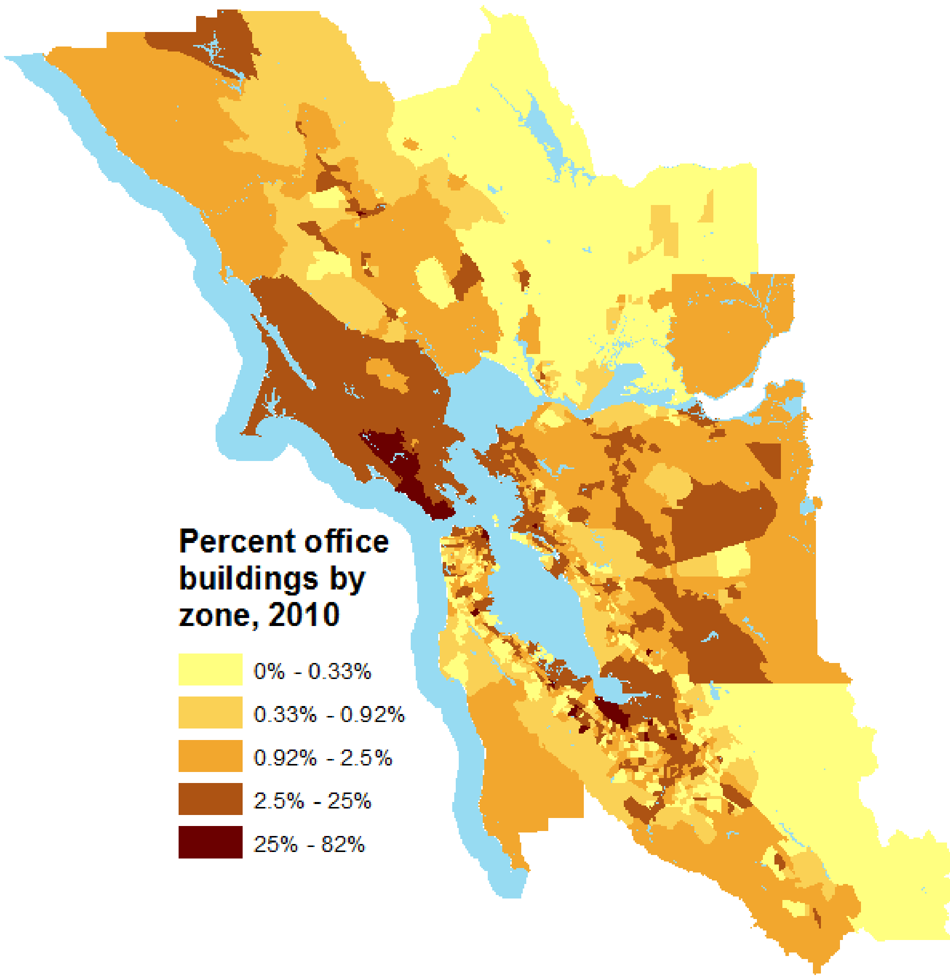


Figure 3.3: Percent Office Buildings, by Zone

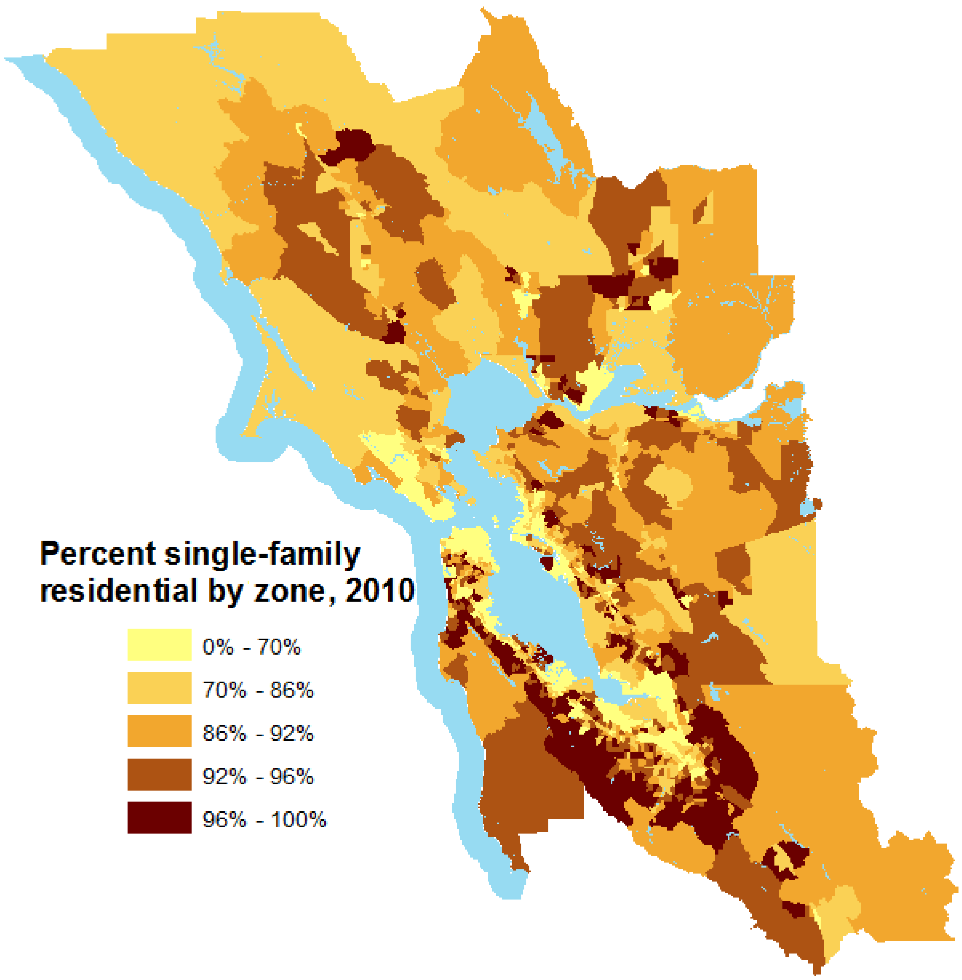


Figure 3.4: Percent SF Residential Buildings, by Zone

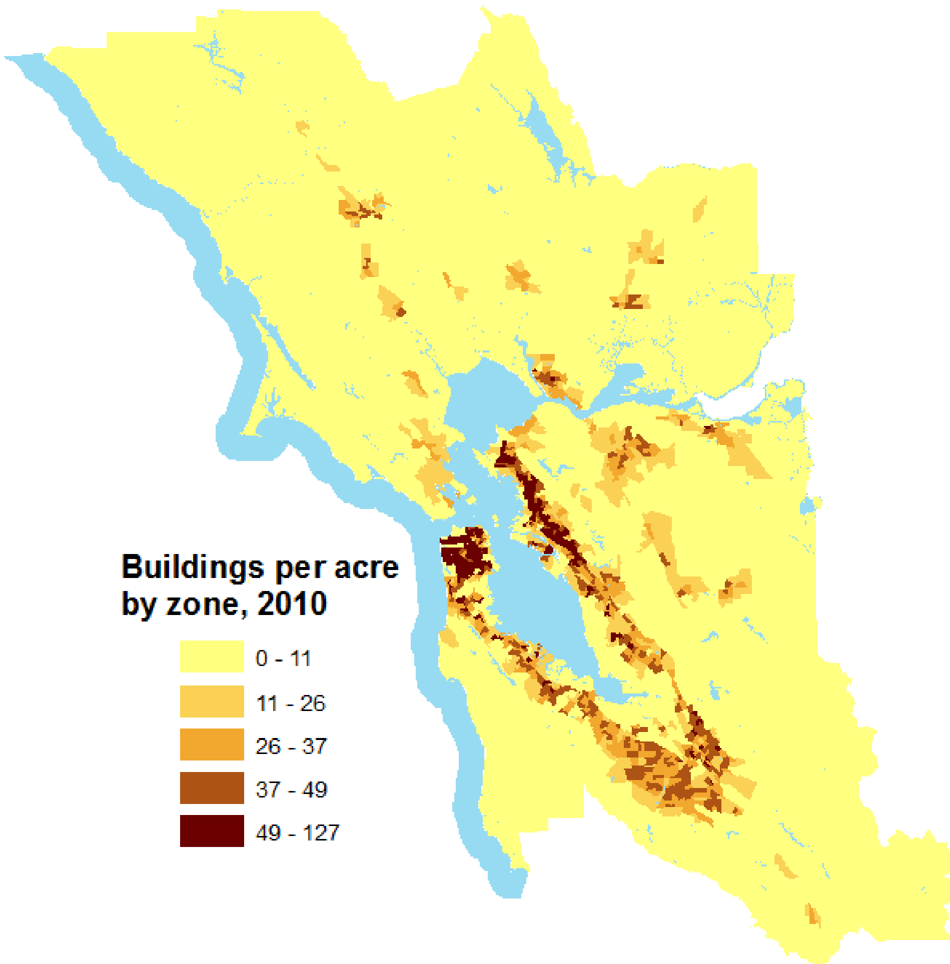


Figure 3.5: Buildings per Acre, by Zone

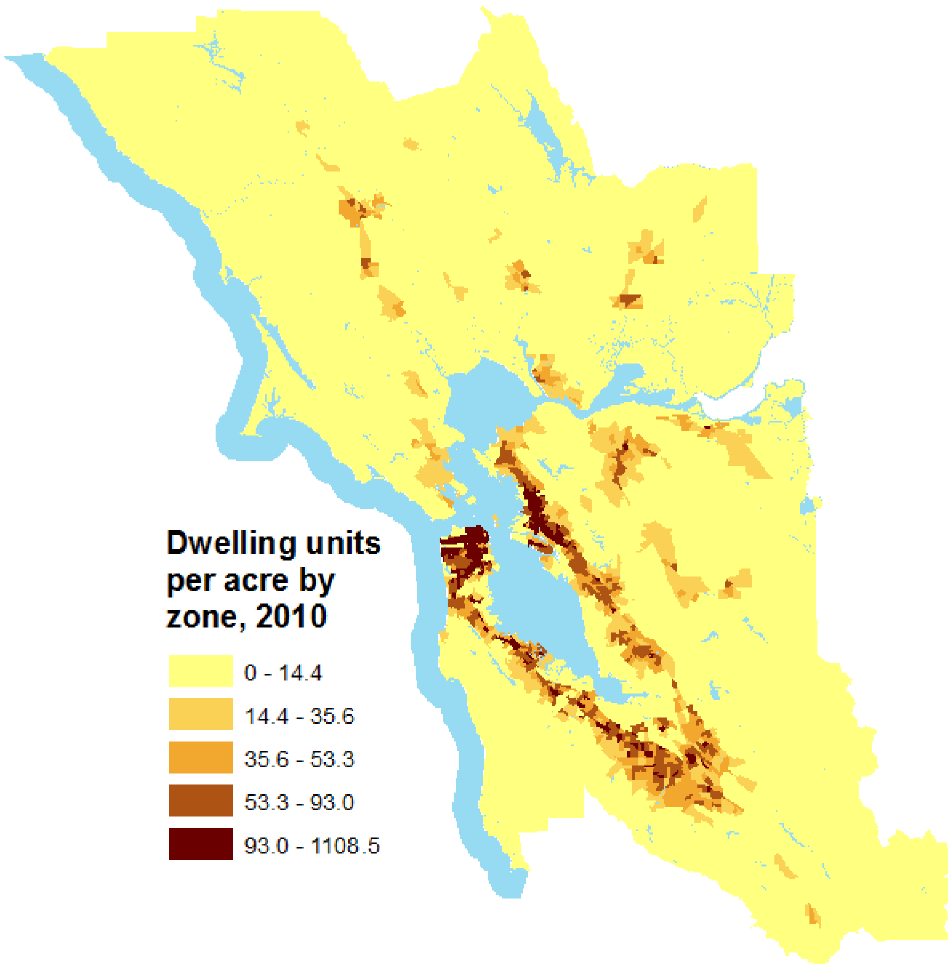


Figure 3.6: Dwelling Units per Acre, by Zone

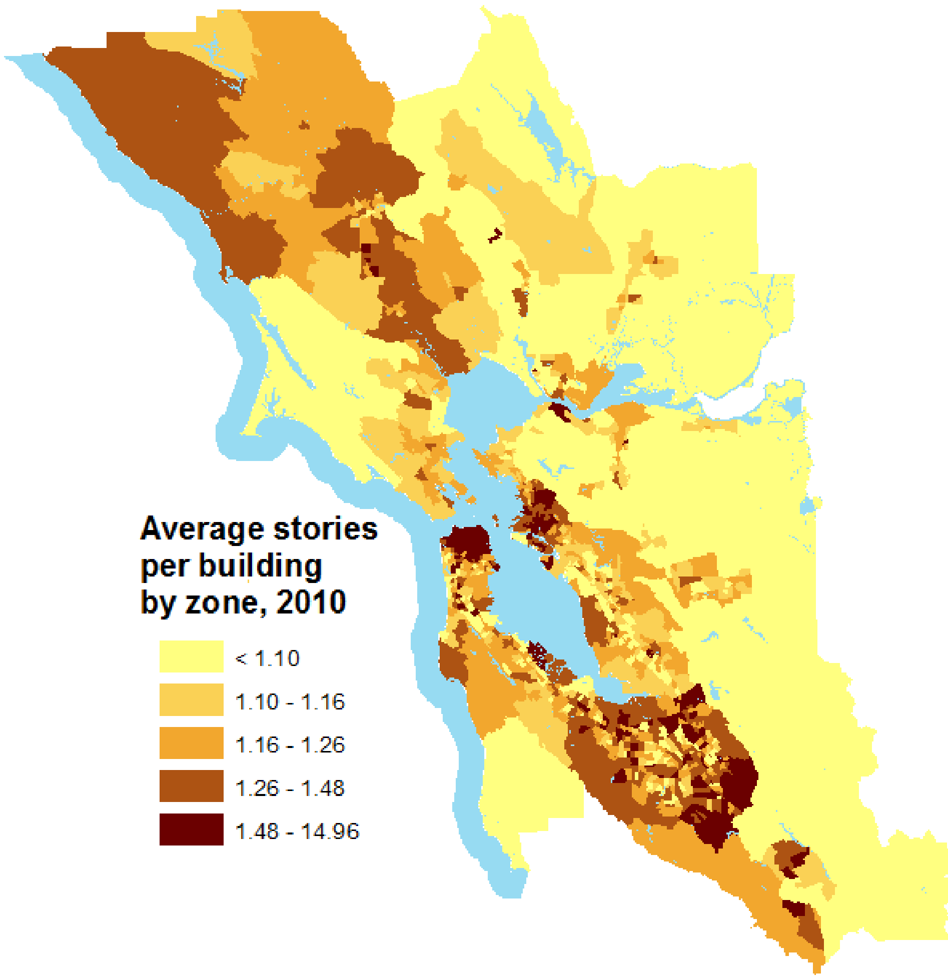


Figure 3.7: Average Number of Stories of Buildings, by Zone

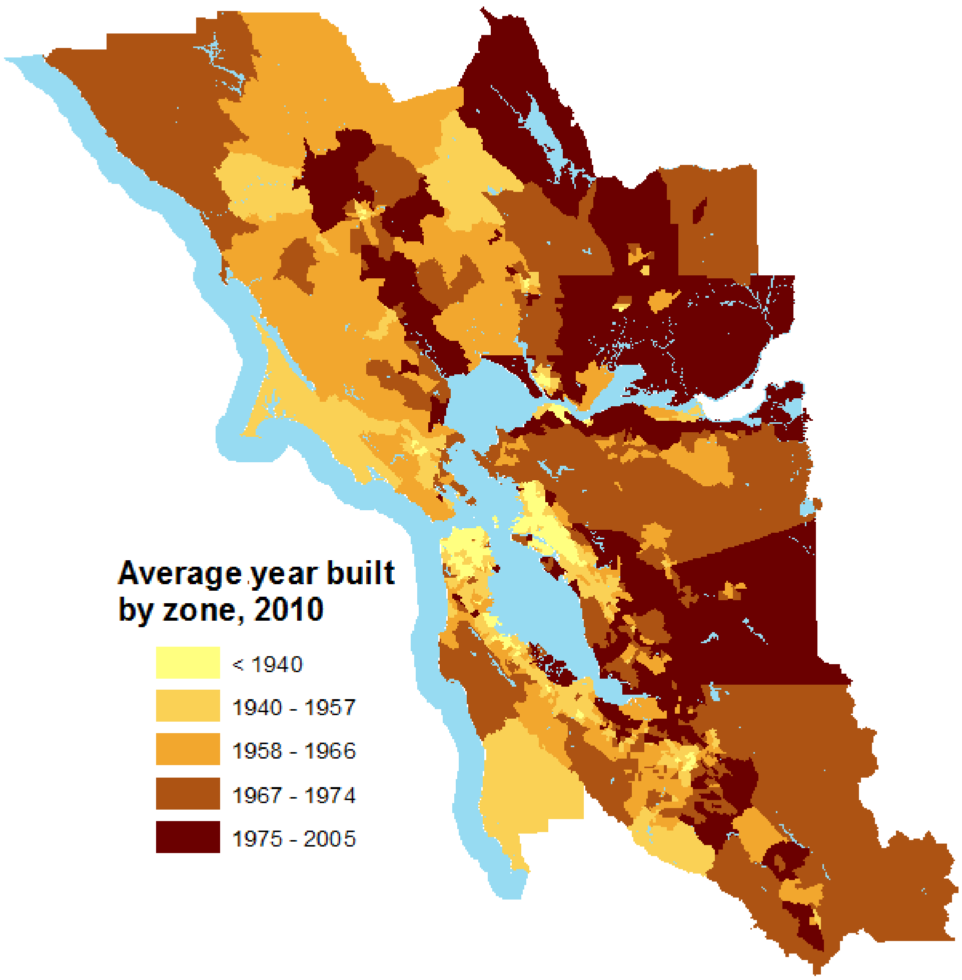


Figure 3.8: Average Year of Building Construction, by Zone

3.6 building_sqft_per_job

This table contains a listing of the non-residential square footage used by jobs in particular building types. It is used by the real estate development model, as well as the business location choice model.

A building_sqft_per_job table has been prepared and formatted for UrbanSim.

Column Name	Data Type	Description
id	integer	unique identifier
employment_submarket_id	integer	the submarket the record applies to
building_type_id	integer	the building type the record applies to
building_sqft_per_employee	integer	the sqft per job each job in a particular building type in a particular zone

3.7 building_types

The building_types table provides a list of unique building types as classified by ABAG. Separate Real Estate Price submodels may be specified for each type of building.

A building_types table has been prepared and formatted for the Bay Area UrbanSim model system. Curently, 16 building types are defined, and it is denoted whether each type 'is residential' and 'has jobs' onsite.

Column Name	Data Type	Description
building_type_id	integer	unique identifier
building_type_name	varchar	name of the building type
building_type_short_name	varchar	abbreviation of the building type name
is_residential	boolean	1 if this building type is residential, 0 otherwise
has_residential	boolean	1 if this building type has a residential component, 0 otherwise

Column Name	Data Type	Description
building_type_id	integer	building type
size_category	varchar	
demolition_cost_per_sqft	integer	cost in dollars per sqft of demolition

3.8 employment_sectors

The employment_sectors table contains categories that represent ABAG-defined aggregations of an industrial classification (e.g. NAICS or SIC). It is used by the employment models, including the Business Location Choice Model, where separate submodels can be specified for each employment sector. Each row in the table defines one Employment Sector.

An employment_secors table has been prepared and formatted. 28 sectors are represented (ABAG's 27-sector definition plus unclassified). These categories map directly to NAICS categories, as well as to Census PUMS ACS definitions of industry and occupation type. These employment sectors were also selected so as to provide a good correspondence to building type-industry usage categories.

Column Name	Data Type	Description
sector_id	integer	Unique identifier
name	varchar	Unique name of the Sector

3.9 households

The household table contains household data, with each row pertaining to one household. The household table is modified by the Household Transition Model, the Household Relocation Model, and the Household Location Choice Model .

Column Name	Data Type	Description
household_id	integer	Unique identifier
building_id	integer	Building this household resides in; -1 if currently not residing in a housing unit
building_typd_id	integer	Building type this household resides in
tenure	integer	rent (1) vs. own (2)
persons	integer	Total number of people living in this household.
workers	integer	Total number of workers living in this household.
age_of_head	integer	Age of head of the household
income	integer	Income of this household
children	integer	Number of children living in this household
race_id	integer	Race of head of household
cars	integer	Number of cars in this household

A household table has been prepared and formatted for UrbanSim. Households in the table were synthesized by MTC from Census 2000 PUMS and SF3 tables using the MTC population synthesizer. The households table was then updated to reflect observed 2010 data.

2,616,085 households are in the base-year households table. The mean persons per household is 2.7. The mean number of household workers is 1.39. The mean age of household head is 48.6 years. The mean number of household vehicles is 1.77. The mean household income is $81,937. The mean number of household children is 0.53.

Figures 3.9 and 3.10 map out selected household table attributes at the zonal level.

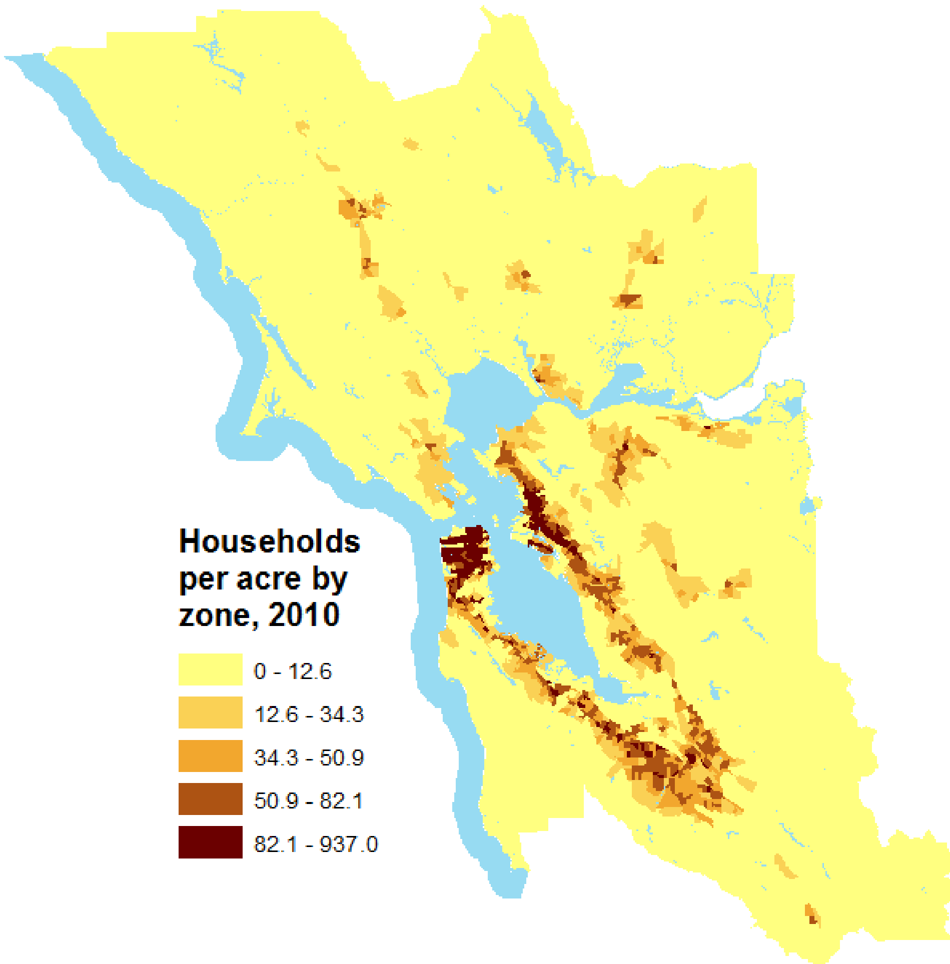


Figure 3.9: Synthesized Households per Acre, by Zone

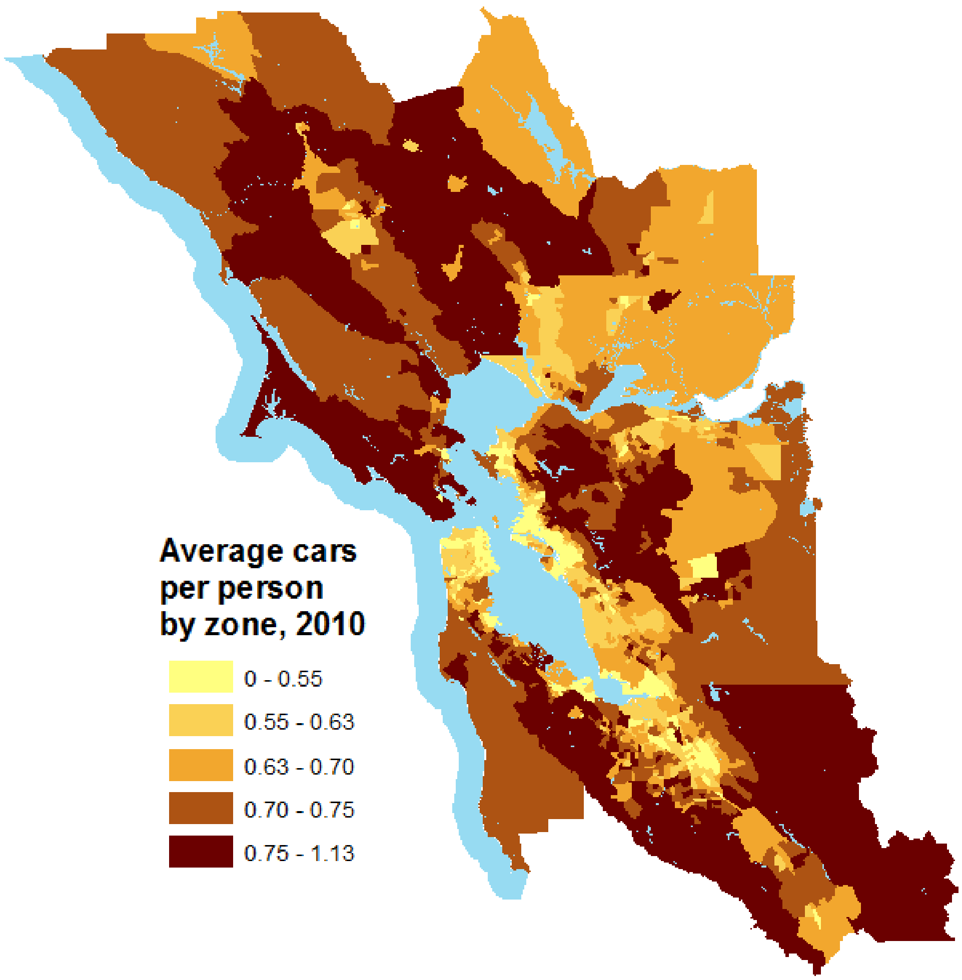


Figure 3.10: Average Household Vehicles per Person, by Zone

3.10 establishments

The establishments table contains an inventory of establishments and jobs in the region. Each row pertains to one establishment. This table is modified by the Employment Transition Model, the Employment Relocation Model, and the Employment Location Choice Model.

An establishments table has been prepared for ABAG by geocoding establishment records to specific buildings.

Column Name	Data Type	Description
establishment_id	integer	Unique identifier
sector_id	integer	Sector this establishment belongs to
employment_submarket_id	integer	Employment submarket this establishment belongs to
employees	integer	Number of employees associated with this establishment
building_id	integer	Building this establishment exists in
last_move_year	integer	Year this establishment last moved
home_based	boolean	True if home-based
parcel_id	integer	Parcel this establishment is based on
zone_id	integer	Zone this establishment is based on
duns_number	integer	D-U-N-S number

3.11 parcels

The parcels table contains the attributes of individual parcels. Each parcel may be associated with 0,1, or more buildings. In general, the parcel table will have an identifier for every other level of geography for aggregation purposes. Attributes include parcel_id, parcel_sqft, and geographic identifiers.

Column Name	Data Type	Description
parcel_id	integer	unique identifier
county_id	integer	id number for the county where the parcel is located
zone_id	integer	id number for the zone that the parcel's centroid falls within
city_id	integer	id number for the city where the parcel is located
pda_id	integer	id number for the priority development area (PDA) where the parcel is located (-1 if not located in a PDA)
area_permutation_hc_id	integer	id number for the area permutation where the parcel is located
superdistrict_id	integer	id number for the superdistrict where ths parcel is located
blockface_id	integer	id number for the Census block-face where the parcel is located
block_id	integer	id number for the Census block where the parcel is located
tpp_id	integer	id number for the TPP where the parcel is located (-1 if not located in a TPP)
jurisdiction_id	integer	id number for the jurisdiction where the parcel is located
node_id	integer	id number for the node where the parcel is located
schooldistrict_id	integer	id number for the school district where the parcel is located
shape_area	integer	shape area of the parcel

A parcel table has been prepared and formatted for UrbanSim. It was created from parcel/property/land-use data files sent by ABAG. The parcel table contains 2,023,878 records.

3.12 persons

The persons table contains the synthesized population for the region, linked to households. Each row pertains to one person.

A person table has been prepared and formatted for the Bay Area. Persons in the table were synthesized for the Bay Area region from Census 2000 PUMS and SF3 tables using the MTC population synthesizer. The persons table was updated to reflect observed 2010 data. Current attributes include person_id, household_id, age, gender, race, worker dummy, earnings, education, school_enrollment, and various geographic identifiers.

7,460,811 persons are in the base year persons table. The mean age is 35.81, and the age distribution is shown in Figure 3.11 . The population is split evenly by gender- 49.9% male and 51.1% female.

Figure 3.12 maps out synthesized persons at the zonal level.

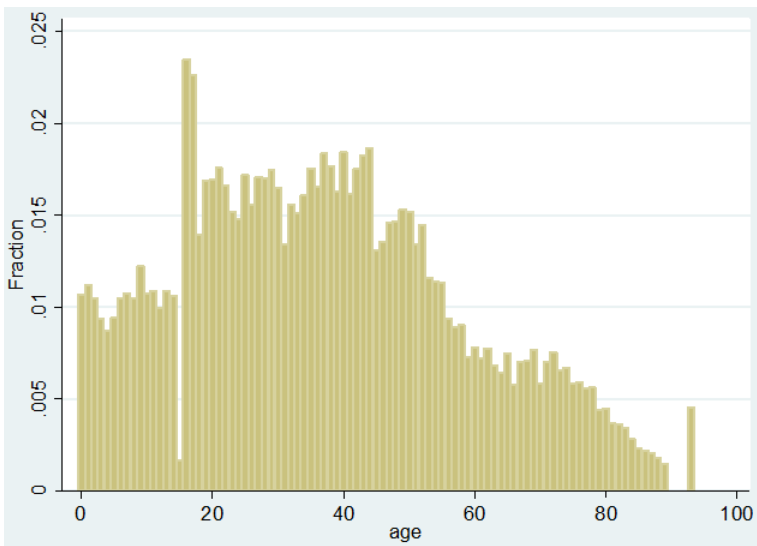


Figure 3.11: Persons by age in the synthetic population

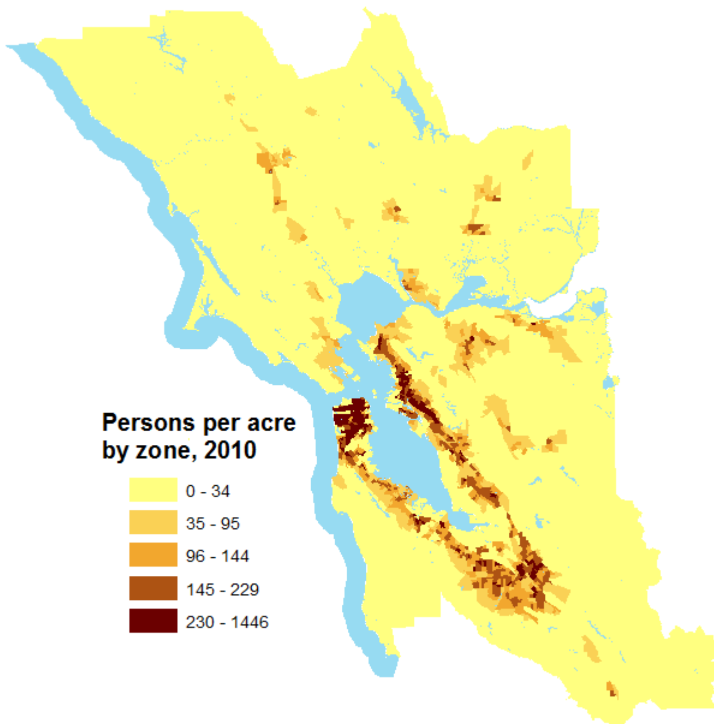


Figure 3.12: Synthesized Persons per Acre, by Zone

3.13 geography_zoning

The geography_zoning table (a database table that is not cached) contains the list of zoning designations, reflecting some classification of land use regulations defining permissible uses and densities of future development. Each record in the table represents a set of rules that restrict development in specific ways. It is used by the the developer model to determine what buildings can be constructed on each parcel. Table attributes include maximum FAR, maximum building height, front/side/rear setbacks, minimum lot size, and maximum parcel coverage.

Column Name	Data Type	Description
id	integer	Unique zoning identification number
name	string (14)	Name of zoning classification
min_far	float	Minimum FAR, if applicable
max_far	float	Maximum FAR, if applicable
max_height	float	Maximum building height in feet
min_dua	float	Minimum residential units per acre, if applicable
max_dua	float	Maximum residential units per acre, if applicable
min_lot_size	float	Minimum lot size in square feet
coverage	float	Maximum proportion of parcel land area that can be developed
max_du_per_parcel	float	Maximum number of residential units that can be built per parcel
min_front_setback	float	Minimum building setback from front of parcel, in feet
max_front_setback	float	Maximum building setback from front of parcel, in feet
side_setback	float	Minimum building setback from sides of parcel, in feet
rear_setback	float	Minimum building setback from rear of parcel, in feet
city	integer	Id of city where zoning classification is applicable

3.14 geography_building_type_zone_relation

The geography_building_type_zone_relation table specifies the allowable building types that may be constructed in each zoning category found in the geography_zoning table. Each row represents one zoning-category/building-type pair.

Column Name	Data Type	Description
zoning_id	integer	a zoning id from plan_types table
building_type	integer	a building type id from the building_types table

3.15 zone_accessibility

The zone_accessibility table contains zonal accessibility variables. It is used to store travel-model generated accessibility variables used by various models.

This table can be updated with the results of any travel model run.

Column Name	Data Type	Description
zone_id	integer	Unique identifier

3.16 zones

The zones table contains a list of traffic analysis zones used in the travel model. The current 1454 ABAG/ MTC zone system is used. Characteristics of each zone are also added to this table.

Column Name	Data Type	Description
zone_id	integer	Unique identifier

CHAPTER

FOUR

Model Estimation for the Bay Area

This chapter documents the specification, estimation, calibration and validation of the UrbanSim model components for the Bay Area region. The first sections present model estimation results. This is organized according to the different UrbanSim models that require statistical estimation of parameters. For each model, model structure and data are briefly reviewed, followed by a description of the model specification and estimation results for the model equations. All estimated coefficients were generated within UrbanSim.

After estimation results are presented, the calibration and validation process is discussed. Model estimation was followed by 1-year simulation runs to compare output with validation targets. Models were calibrated in order to better account for target changes. Next, 30-year simulations were run to gauge the model's policy sensitivities. Model calibration, validation, and sensitivity analyses were highly inter-connected procedures, due to UrbanSim model components having a high degree of mutual influence. Adjusting one model might necessitate the re-calibration of a separate model; the whole process was iterative and inter-dependent.

4.1 Household Location Choice

The Household Location Choice Model (HLCM) predicts the probability that a household that is either new (from the Household Transition model) or has decided to move within the region (from the Household Relocation model) will choose a particular submarket location. The model is specified as a multinomial logit (MNL) with sampling of alternatives from the universe of submarkets to estimate model coefficients. Submarkets are defined as school-district/residential-building-type/tenure/transit-proximity combinations. After submarkets are predicted for households (using Monte Carlo simulation), the choice of a specific building within the submarket is predicted.

The model is stratified into submodels by household income, size, and tenure (4 income categories, 3 household size categories, and 2 tenure categories, for a total of 24 submodels). Explanatory variables used in the model include accessibility, attributes of housing, price, and interaction terms between household and location attributes.

The location choice set consists of submarket alternatives. Submarkets are defined by school district, residential building type, tenure, and transit proximity combinations. The submarket dataset is automatically generated from the parcel-level building data, so the number of submarkets in the region can evolve over time if areas take on new building types.

Model coefficients were estimated using data from the synthetic households table for the Bay Area. For the majority of submodels (except when the sample size was too small), only households that had moved within the previous five years (as identified in the PUMS record) were used for estimation. The restriction to households which had moved within the past 5 years was made to reflect the choices of households in similar circumstances to those being modeled (household that are relocating or moving into the region).

Household location choice is represented for the Bay Area by a sequence of choice models. The models are, in order: tenure choice, submarket choice, and building choice. This is the order in which the models are simulated. The first choice model represents a binary household choice of 'rent' vs. 'own'. Tenure model coefficients are shown in Table 4.1. Next, the choice of submarket is modeled, conditional on the previously modeled tenure dimension. Tables 4.2 to 4.25 below list the coefficients for the submodels, each of which was specified independently. Variable sets were somewhat similar across submodels, although there was variation owing to the principal that households in different sumbmodels might predicate their location choice on different factors. The final model in the sequence of models that represents household location choice is a simple location choice model that allocates households to specific buildings within the chosen submarket.

In the tenure choice model, children, age of head, and income are hypothesized to be positively associated with home-ownership. In the submarket household locaation choice models, the location choice of owner-households is hypothesized to be positively associated with single-family submarkets (and the opposite association is likely to be seen for renters), a negative association with price is hypothesized across all submodels, and, other things equal,a positive association with accessibility, square footage, residential units, and income is hypothesized across all submodels. For some variables, variation in coefficient sign is expected, as the correlations between household location choice and specific variables will vary by submodel (recall that submodels reflect household income, size, and tenure categories) and in some cases variables may be proxying for the effect of an unobserved variable.

Table 4.1: Tenure Choice Model Coefficients

Coefficient Name	Estimate	Standard Error	T-Statistic
hh_children	0.0528	0.01286	4.10757
hh_head65	-0.4766	0.06162	-7.73455
hh_head_age	0.05988	0.00135	44.21329
ln_hh_income	0.31233	0.00704	44.38535
constant	-4.80851	0.1014	-47.41976

Table 4.2: Submodel 1 - Household Location Choice Model - Owner Coefficients

Coefficient Name	Estimate	Standard Error	T-Statistic
is_single_family_submarket	1.71744	0.22576	7.60734
ln_avg_sale_price	-0.44035	0.0379	-11.61844
ln_median_income	0.0964	0.16003	0.60239
ln_median_lot_sqft	-0.37356	0.03701	-10.0943
ln_median_sqft	-0.00764	0.02353	-0.32474
ln_residential_units	0.20493	0.02426	8.4478
median_age_of_head	0.06093	0.01141	5.33858
median_household_size	-0.27251	0.07333	-3.71648
proportion_single_person_households	3.4289	0.81048	4.23072
submarket_avg_auto_peak_total_access	0.08771	0.03979	2.2043
county_is_alameda_calib	-0.9	1	1
county_is_contracosta_calib	-1.8	1	1
county_is_marin_calib	-2.65	1	1
county_is_napa_calib	-2.4	1	1
county_is_sanmateo_calib	-0.5	1	1
county_is_santaclara_calib	-0.7	1	1
county_is_solano_calib	-1.7	1	1
county_is_sonoma_calib	-2.9	1	1

Table 4.3: Submodel 2 - Household Location Choice Model - Owner Coefficients

Coefficient Name	Estimate	Standard Error	T-Statistic
is_single_family_submarket	1.68862	0.23392	7.2187
ln_avg_sale_price	-0.5016	0.05029	-9.97478
ln_median_income	0.44197	0.18302	2.41483
ln_median_lot_sqft	-0.48275	0.04147	-11.64127
ln_median_sqft	-0.06711	0.0261	-2.57165
ln_residential_units	0.14853	0.02739	5.42277
median_age_of_head	0.06294	0.01242	5.06929
median_household_size	-0.16941	0.08527	-1.98688
proportion_single_person_households	4.40545	0.84834	5.19305
submarket_avg_auto_peak_total_access	0.08478	0.04661	1.81897
county_is_alameda_calib	-0.9	1	1
county_is_contracosta_calib	-1.8	1	1
county_is_marin_calib	-2.65	1	1
county_is_napa_calib	-2.4	1	1
county_is_sanmateo_calib	-0.5	1	1
county_is_santaclara_calib	-0.7	1	1
county_is_solano_calib	-1.7	1	1
county_is_sonoma_calib	-2.9	1	1

Table 4.4: Submodel 3 - Household Location Choice Model - Owner Coefficients

Coefficient Name	Estimate	Standard Error	T-Statistic
is_single_family_submarket	1.99034	0.23116	8.61017
ln_avg_sale_price	-0.51135	0.05339	-9.57828
ln_median_income	0.63309	0.18787	3.36992
ln_median_lot_sqft	-0.4603	0.04082	-11.27577
ln_median_sqft	-0.06567	0.02631	-2.49559
ln_residential_units	0.24036	0.02789	8.61697
median_age_of_head	0.0409	0.01309	3.12507
median_household_size	-0.13755	0.08434	-1.6309
proportion_single_person_households	5.98178	0.8583	6.96933
submarket_avg_auto_peak_total_access	0.09192	0.04745	1.93716
county_is_alameda_calib	-0.9	1	1
county_is_contracosta_calib	-1.8	1	1
county_is_marin_calib	-2.65	1	1
county_is_napa_calib	-2.4	1	1
county_is_sanmateo_calib	-0.5	1	1
county_is_santaclara_calib	-0.7	1	1
county_is_solano_calib	-1.7	1	1
county_is_sonoma_calib	-2.9	1	1

Table 4.5: Submodel 4 - Household Location Choice Model - Owner Coefficients

Coefficient Name	Estimate	Standard Error	T-Statistic
is_single_family_submarket	1.62362	0.2377	6.83053
ln_avg_sale_price	-0.48333	0.05255	-9.1975
ln_median_income	2.04434	0.1812	11.28226
ln_median_lot_sqft	-0.59079	0.04814	-12.27127
ln_median_sqft	-0.05453	0.03018	-1.80694
ln_residential_units	0.30426	0.02897	10.50306
median_age_of_head	0.05825	0.01384	4.20729
median_household_size	-0.24404	0.09666	-2.5247
median_year_built	-0.00025	0.00014	-1.72993
proportion_single_person_households	7.35139	0.97024	7.57687
submarket_avg_auto_peak_total_access	0.21812	0.05348	4.07883
county_is_alameda_calib	-0.9	1	1
county_is_contracosta_calib	-1.8	1	1
county_is_marin_calib	-2.65	1	1
county_is_napa_calib	-2.4	1	1
county_is_sanmateo_calib	-0.5	1	1
county_is_santaclara_calib	-0.7	1	1
county_is_solano_calib	-1.7	1	1
county_is_sonoma_calib	-2.9	1	1

Table 4.6: Submodel 5 - Household Location Choice Model - Owner Coefficients

Coefficient Name	Estimate	Standard Error	T-Statistic
is_single_family_submarket	1.86126	0.25468	7.30826
ln_avg_sale_price	-0.47489	0.06539	-7.26248
ln_median_income	-0.72493	0.23084	-3.14042
ln_median_lot_sqft	-0.19342	0.05868	-3.2962
ln_median_sqft	-0.04198	0.03694	-1.13633
ln_residential_units	0.12254	0.03511	3.48979
median_age_of_head	0.0401	0.01668	2.40462
median_household_size	-0.09451	0.08026	-1.17757
submarket_avg_auto_peak_total_access	0.22091	0.06087	3.62926
county_is_alameda_calib	-0.9	1	1
county_is_contracosta_calib	-1.8	1	1
county_is_marin_calib	-2.65	1	1
county_is_napa_calib	-2.4	1	1
county_is_sanmateo_calib	-0.5	1	1
county_is_santaclara_calib	-0.7	1	1
county_is_solano_calib	-1.7	1	1
county_is_sonoma_calib	-2.9	1	1

Table 4.7: Submodel 6 - Household Location Choice Model - Owner Coefficients

Coefficient Name	Estimate	Standard Error	T-Statistic
is_single_family_submarket	2.09224	0.22039	9.49345
ln_avg_sale_price	-0.48741	0.04685	-10.40411
ln_median_income	-0.53607	0.19116	-2.80436
ln_median_lot_sqft	-0.30067	0.04711	-6.38259
ln_median_sqft	-0.09723	0.03128	-3.10854
ln_residential_units	0.16957	0.02924	5.79919
median_age_of_head	0.05345	0.01256	4.25622
median_household_size	-0.3863	0.06575	-5.87511
submarket_avg_auto_peak_total_access	-0.05223	0.04615	-1.13185
county_is_alameda_calib	-0.9	1	1
county_is_contracosta_calib	-1.8	1	1
county_is_marin_calib	-2.65	1	1
county_is_napa_calib	-2.4	1	1
county_is_sanmateo_calib	-0.5	1	1
county_is_santaclara_calib	-0.7	1	1
county_is_solano_calib	-1.7	1	1
county_is_sonoma_calib	-2.9	1	1

Table 4.8: Submodel 7 - Household Location Choice Model - Owner Coefficients

Coefficient Name	Estimate	Standard Error	T-Statistic
is_single_family_submarket	1.23399	0.15369	8.02926
ln_avg_sale_price	-0.45596	0.03362	-13.56052
ln_median_income	0.20302	0.13683	1.48379
ln_median_lot_sqft	-0.17562	0.04134	-4.2482
ln_median_sqft	0.04893	0.02357	2.07568
ln_residential_units	0.09271	0.02074	4.47004
median_age_of_head	0.03802	0.01011	3.75961
median_household_size	-0.10861	0.04748	-2.28748
submarket_avg_auto_peak_total_access	0.17403	0.03505	4.96558
county_is_alameda_calib	-0.9	1	1
county_is_contracosta_calib	-1.8	1	1
county_is_marin_calib	-2.65	1	1
county_is_napa_calib	-2.4	1	1
county_is_sanmateo_calib	-0.5	1	1
county_is_santaclara_calib	-0.7	1	1
county_is_solano_calib	-1.7	1	1
county_is_sonoma_calib	-2.9	1	1

Table 4.9: Submodel 8 - Household Location Choice Model - Owner Coefficients

Coefficient Name	Estimate	Standard Error	T-Statistic
is_single_family_submarket	0.78212	0.09813	7.97
ln_avg_sale_price	-0.35139	0.01876	-18.73154
ln_median_income	1.39785	0.08435	16.5716
ln_median_lot_sqft	-0.36089	0.02489	-14.50156
ln_median_sqft	0.00284	0.01608	0.17636
ln_residential_units	0.14115	0.01401	10.07131
median_age_of_head	0.0373	0.00649	5.74846
median_household_size	-0.33446	0.03245	-10.30654
submarket_avg_auto_peak_total_access	0.12949	0.02534	5.10943
county_is_alameda_calib	-0.9	1	1
county_is_contracosta_calib	-1.8	1	1
county_is_marin_calib	-2.65	1	1
county_is_napa_calib	-2.4	1	1
county_is_sanmateo_calib	-0.5	1	1
county_is_santaclara_calib	-0.7	1	1
county_is_solano_calib	-1.7	1	1
county_is_sonoma_calib	-2.9	1	1

Table 4.10: Submodel 9 - Household Location Choice Model - Owner Coefficients

Coefficient Name	Estimate	Standard Error	T-Statistic
is_single_family_submarket	2.66004	0.3297	8.06815
ln_avg_sale_price	-0.44733	0.05864	-7.62892
ln_median_income	-1.00791	0.26649	-3.78215
ln_median_lot_sqft	-0.24334	0.08558	-2.84335
ln_median_sqft	0.00779	0.0569	0.13691
ln_residential_units	0.30812	0.04313	7.14379
median_age_of_head	0.03648	0.02013	1.8123
median_household_size	0.0418	0.09167	0.45595
median_year_built	-0.00016	0.00018	-0.94036
submarket_avg_auto_peak_total_access	0.53634	0.07851	6.83138
county_is_alameda_calib	-0.9	1	1
county_is_contracosta_calib	-1.8	1	1
county_is_marin_calib	-2.65	1	1
county_is_napa_calib	-2.4	1	1
county_is_sanmateo_calib	-0.5	1	1
county_is_santaclara_calib	-0.7	1	1
county_is_solano_calib	-1.7	1	1
county_is_sonoma_calib	-2.9	1	1

Table 4.11: Submodel 10 - Household Location Choice Model - Owner Coefficients

Coefficient Name	Estimate	Standard Error	T-Statistic
is_single_family_submarket	2.73826	0.23323	11.74043
ln_avg_sale_price	-0.40612	0.04307	-9.429
ln_median_income	-1.70904	0.2112	-8.0922
ln_median_lot_sqft	-0.07599	0.06197	-1.22633
ln_median_sqft	0.04663	0.03751	1.24306
ln_residential_units	0.2481	0.03193	7.77036
median_age_of_head	0.01671	0.01432	1.16658
median_household_size	0.15037	0.0676	2.22421
submarket_avg_auto_peak_total_access	0.34078	0.05749	5.92754
county_is_alameda_calib	-0.9	1	1
county_is_contracosta_calib	-1.8	1	1
county_is_marin_calib	-2.65	1	1
county_is_napa_calib	-2.4	1	1
county_is_sanmateo_calib	-0.5	1	1
county_is_santaclara_calib	-0.7	1	1
county_is_solano_calib	-1.7	1	1
county_is_sonoma_calib	-2.9	1	1

Table 4.12: Submodel 11 - Household Location Choice Model - Owner Coefficients

Coefficient Name	Estimate	Standard Error	T-Statistic
is_single_family_submarket	2.25454	0.14713	15.32326
ln_avg_sale_price	-0.47648	0.03145	-15.15205
ln_median_income	-0.58163	0.13139	-4.42685
ln_median_lot_sqft	-0.25534	0.03337	-7.6509
ln_median_sqft	0.02442	0.02229	1.09515
ln_residential_units	0.19393	0.01827	10.61304
median_age_of_head	0.01951	0.00854	2.2832
median_household_size	0.22218	0.03894	5.70575
median_year_built	-0.00013	0.00006	-2.06532
submarket_avg_auto_peak_total_access	0.20201	0.03189	6.3352
county_is_alameda_calib	-0.9	1	1
county_is_contracosta_calib	-1.8	1	1
county_is_marin_calib	-2.65	1	1
county_is_napa_calib	-2.4	1	1
county_is_sanmateo_calib	-0.5	1	1
county_is_santaclara_calib	-0.7	1	1
county_is_solano_calib	-1.7	1	1
county_is_sonoma_calib	-2.9	1	1

Table 4.13: Submodel 12 - Household Location Choice Model - Owner Coefficients

Coefficient Name	Estimate	Standard Error	T-Statistic
is_single_family_submarket	1.30417	0.08342	15.63404
ln_avg_sale_price	-0.32335	0.01353	-23.89114
ln_median_income	1.02673	0.0643	15.96794
ln_median_lot_sqft	-0.15312	0.02108	-7.26368
ln_median_sqft	0.09201	0.01395	6.59517
ln_residential_units	0.15379	0.01023	15.02851
median_age_of_head	0.01277	0.005	2.55574
median_household_size	0.17073	0.02204	7.74788
submarket_avg_auto_peak_total_access	0.40583	0.01984	20.45391
county_is_alameda_calib	-0.9	1	1
county_is_contracosta_calib	-1.8	1	1
county_is_marin_calib	-2.65	1	1
county_is_napa_calib	-2.4	1	1
county_is_sanmateo_calib	-0.5	1	1
county_is_santaclara_calib	-0.7	1	1
county_is_solano_calib	-1.7	1	1
county_is_sonoma_calib	-2.9	1	1

Table 4.14: Submodel 1 - Household Location Choice Model - Renter Coefficients

Coefficient Name	Estimate	Standard Error	T-Statistic
is_single_family_submarket	-49.33662	15.73242	-3.13598
ln_avg_rent	-2.30607	0.27749	-8.31042
ln_median_income	-1.98369	0.38439	-5.16067
ln_median_lot_sqft	0.22307	0.03048	7.31807
ln_median_sqft	6.58357	2.10006	3.13495
ln_residential_units	1.70497	0.07041	24.21317
median_year_built	0.00069	0.00008	8.41329
submarket_avg_auto_peak_total_access	0.2796	0.1359	2.05742
county_is_alameda_calib	-0.9	1	1
county_is_contracosta_calib	-1.8	1	1
county_is_marin_calib	-2.65	1	1
county_is_napa_calib	-2.4	1	1
county_is_sanmateo_calib	-0.5	1	1
county_is_santaclara_calib	-0.7	1	1
county_is_solano_calib	-1.7	1	1
county_is_sonoma_calib	-2.9	1	1

Table 4.15: Submodel 2 - Household Location Choice Model - Renter Coefficients

Coefficient Name	Estimate	Standard Error	T-Statistic
is_single_family_submarket	-27.46331	10.73358	-2.55863
ln_avg_rent	-2.10348	0.34831	-6.0391
ln_median_income	0.24048	0.4209	0.57135
ln_median_lot_sqft	0.21486	0.03354	6.4055
ln_median_sqft	3.5181	1.45465	2.41852
ln_residential_units	1.58428	0.09185	17.24826
median_year_built	0.00061	0.00009	6.66914
submarket_avg_auto_peak_total_access	-0.19531	0.17586	-1.11059
county_is_alameda_calib	-0.9	1	1
county_is_contracosta_calib	-1.8	1	1
county_is_marin_calib	-2.65	1	1
county_is_napa_calib	-2.4	1	1
county_is_sanmateo_calib	-0.5	1	1
county_is_santaclara_calib	-0.7	1	1
county_is_solano_calib	-1.7	1	1
county_is_sonoma_calib	-2.9	1	1

Table 4.16: Submodel 3 - Household Location Choice Model - Renter Coefficients

Coefficient Name	Estimate	Standard Error	T-Statistic
is_single_family_submarket	-82.94025	29.46636	-2.81474
ln_avg_rent	-3.1692	0.54009	-5.8679
ln_median_income	2.46983	0.5995	4.1198
ln_median_lot_sqft	0.20346	0.05528	3.68034
ln_median_sqft	10.69258	3.95712	2.70211
ln_residential_units	1.58801	0.12393	12.81378
median_year_built	0.00065	0.00013	5.17189
submarket_avg_auto_peak_total_access	-0.17919	0.25707	-0.69705
county_is_alameda_calib	-0.9	1	1
county_is_contracosta_calib	-1.8	1	1
county_is_marin_calib	-2.65	1	1
county_is_napa_calib	-2.4	1	1
county_is_sanmateo_calib	-0.5	1	1
county_is_santaclara_calib	-0.7	1	1
county_is_solano_calib	-1.7	1	1
county_is_sonoma_calib	-2.9	1	1

Table 4.17: Submodel 4 - Household Location Choice Model - Renter Coefficients

Coefficient Name	Estimate	Standard Error	T-Statistic
is_single_family_submarket	-7.03252	0.468	-15.02671
ln_avg_rent	-2.15289	0.20801	-10.35004
ln_median_income	2.86519	0.42658	6.71668
ln_median_lot_sqft	0.87813	0.04447	19.74783
ln_residential_units	1.41582	0.11348	12.47614
median_year_built	0.00337	0.00013	25.45209
submarket_avg_auto_peak_total_access	-0.4502	0.26289	-1.71251
county_is_alameda_calib	-0.9	1	1
county_is_contracosta_calib	-1.8	1	1
county_is_marin_calib	-2.65	1	1
county_is_napa_calib	-2.4	1	1
county_is_sanmateo_calib	-0.5	1	1
county_is_santaclara_calib	-0.7	1	1
county_is_solano_calib	-1.7	1	1
county_is_sonoma_calib	-2.9	1	1

Table 4.18: Submodel 5 - Household Location Choice Model - Renter Coefficients

Coefficient Name	Estimate	Standard Error	T-Statistic
is_single_family_submarket	-11.19277	4.22949	-2.64636
ln_avg_rent	-2.71806	0.49295	-5.51387
ln_median_income	-3.29094	0.49853	-6.60131
ln_median_lot_sqft	0.22588	0.04294	5.26014
ln_median_sqft	1.52275	0.54835	2.77697
ln_residential_units	1.77082	0.11796	15.01192
median_year_built	0.00065	0.00011	5.86101
submarket_avg_auto_peak_total_access	0.43083	0.18891	2.28061
county_is_alameda_calib	-0.9	1	1
county_is_contracosta_calib	-1.8	1	1
county_is_marin_calib	-2.65	1	1
county_is_napa_calib	-2.4	1	1
county_is_sanmateo_calib	-0.5	1	1
county_is_santaclara_calib	-0.7	1	1
county_is_solano_calib	-1.7	1	1
county_is_sonoma_calib	-2.9	1	1

Table 4.19: Submodel 6 - Household Location Choice Model - Renter Coefficients

Coefficient Name	Estimate	Standard Error	T-Statistic
is_single_family_submarket	-108.13213	21.29703	-5.07733
ln_avg_rent	-5.10417	0.49965	-10.21542
ln_median_income	-0.34228	0.47215	-0.72495
ln_median_sqft	14.31135	2.83934	5.04038
ln_residential_units	2.11889	0.10111	20.9554
median_year_built	0.00063	0.00011	5.79608
submarket_avg_auto_peak_total_access	0.87068	0.19692	4.42151
county_is_alameda_calib	-0.9	1	1
county_is_contracosta_calib	-1.8	1	1
county_is_marin_calib	-2.65	1	1
county_is_napa_calib	-2.4	1	1
county_is_sanmateo_calib	-0.5	1	1
county_is_santaclara_calib	-0.7	1	1
county_is_solano_calib	-1.7	1	1
county_is_sonoma_calib	-2.9	1	1

Table 4.20: Submodel 7 - Household Location Choice Model - Renter Coefficients

Coefficient Name	Estimate	Standard Error	T-Statistic
is_single_family_submarket	-15.48125	10.25219	-1.51004
ln_avg_rent	-1.85928	0.36339	-5.1165
ln_median_income	-0.3692	0.46099	-0.80087
ln_median_lot_sqft	0.28396	0.03549	8.00081
ln_median_sqft	1.88601	1.392	1.35489
ln_residential_units	1.465	0.09098	16.10168
median_year_built	0.00098	0.00011	9.03581
submarket_avg_auto_peak_total_access	-0.01178	0.19512	-0.06038
county_is_alameda_calib	-0.9	1	1
county_is_contracosta_calib	-1.8	1	1
county_is_marin_calib	-2.65	1	1
county_is_napa_calib	-2.4	1	1
county_is_sanmateo_calib	-0.5	1	1
county_is_santaclara_calib	-0.7	1	1
county_is_solano_calib	-1.7	1	1
county_is_sonoma_calib	-2.9	1	1

Table 4.21: Submodel 8 - Household Location Choice Model - Renter Coefficients

Coefficient Name	Estimate	Standard Error	T-Statistic
is_single_family_submarket	-88.98542	31.05302	-2.8656
ln_avg_rent	-3.58663	0.39686	-9.03744
ln_median_income	2.66799	0.50958	5.23565
ln_median_lot_sqft	0.20344	0.04117	4.94167
ln_median_sqft	11.51784	4.16835	2.76316
ln_residential_units	1.79409	0.09248	19.39986
median_year_built	0.00068	0.0001	6.57533
submarket_avg_auto_peak_total_access	0.01383	0.24346	0.05681
county_is_alameda_calib	-0.9	1	1
county_is_contracosta_calib	-1.8	1	1
county_is_marin_calib	-2.65	1	1
county_is_napa_calib	-2.4	1	1
county_is_sanmateo_calib	-0.5	1	1
county_is_santaclara_calib	-0.7	1	1
county_is_solano_calib	-1.7	1	1
county_is_sonoma_calib	-2.9	1	1

Table 4.22: Submodel 9 - Household Location Choice Model - Renter Coefficients

Coefficient Name	Estimate	Standard Error	T-Statistic
is_single_family_submarket	-47.1172	10.97871	-4.29169
ln_avg_rent	-2.89596	0.36522	-7.92926
ln_median_income	-3.88444	0.44015	-8.82521
ln_median_lot_sqft	0.21657	0.0366	5.91657
ln_median_sqft	6.45218	1.47869	4.36344
ln_residential_units	1.97979	0.10571	18.72763
median_year_built	0.00063	0.0001	6.11185
submarket_avg_auto_peak_total_access	0.82693	0.19524	4.23544
county_is_alameda_calib	-0.9	1	1
county_is_contracosta_calib	-1.8	1	1
county_is_marin_calib	-2.65	1	1
county_is_napa_calib	-2.4	1	1
county_is_sanmateo_calib	-0.5	1	1
county_is_santaclara_calib	-0.7	1	1
county_is_solano_calib	-1.7	1	1
county_is_sonoma_calib	-2.9	1	1

Table 4.23: Submodel 10 - Household Location Choice Model - Renter Coefficients

Coefficient Name	Estimate	Standard Error	T-Statistic
is_single_family_submarket	-17.23904	9.77127	-1.76426
ln_avg_rent	-2.08884	0.3681	-5.67473
ln_median_income	-2.04757	0.42055	-4.86881
ln_median_lot_sqft	0.24324	0.03343	7.27635
ln_median_sqft	2.3227	1.32647	1.75104
ln_residential_units	1.72643	0.0982	17.58027
median_year_built	0.00075	0.0001	7.73172
submarket_avg_auto_peak_total_access	0.28946	0.18519	1.56303
county_is_alameda_calib	-0.9	1	1
county_is_contracosta_calib	-1.8	1	1
county_is_marin_calib	-2.65	1	1
county_is_napa_calib	-2.4	1	1
county_is_sanmateo_calib	-0.5	1	1
county_is_santaclara_calib	-0.7	1	1
county_is_solano_calib	-1.7	1	1
county_is_sonoma_calib	-2.9	1	1

Table 4.24: Submodel 11 - Household Location Choice Model - Renter Coefficients

Coefficient Name	Estimate	Standard Error	T-Statistic
is_single_family_submarket	-14.37618	4.10068	-3.50581
ln_avg_rent	-2.2236	0.38554	-5.76751
ln_median_income	0.24072	0.3953	0.60894
ln_median_lot_sqft	0.2232	0.02915	7.65734
ln_median_sqft	1.79825	0.5635	3.19121
ln_residential_units	1.68759	0.08479	19.90401
median_year_built	0.00068	0.00009	7.67789
submarket_avg_auto_peak_total_access	-0.11604	0.1872	-0.61988
county_is_alameda_calib	-0.9	1	1
county_is_contracosta_calib	-1.8	1	1
county_is_marin_calib	-2.65	1	1
county_is_napa_calib	-2.4	1	1
county_is_sanmateo_calib	-0.5	1	1
county_is_santaclara_calib	-0.7	1	1
county_is_solano_calib	-1.7	1	1
county_is_sonoma_calib	-2.9	1	1

Table 4.25: Submodel 12 - Household Location Choice Model - Renter Coefficients

Coefficient Name	Estimate	Standard Error	T-Statistic
is_single_family_submarket	-25.3638	5.05925	-5.01335
ln_avg_rent	-2.13844	0.47891	-4.46519
ln_median_income	2.05841	0.47756	4.31028
ln_median_lot_sqft	0.20801	0.0495	4.20183
ln_median_sqft	3.20882	0.69684	4.60479
ln_residential_units	1.82891	0.10902	16.77642
median_year_built	0.00083	0.00012	7.13177
submarket_avg_auto_peak_total_access	-0.45989	0.21467	-2.14226
county_is_alameda_calib	-0.9	1	1
county_is_contracosta_calib	-1.8	1	1
county_is_marin_calib	-2.65	1	1
county_is_napa_calib	-2.4	1	1
county_is_sanmateo_calib	-0.5	1	1
county_is_santaclara_calib	-0.7	1	1
county_is_solano_calib	-1.7	1	1
county_is_sonoma_calib	-2.9	1	1

4.2 Business Location Choice

In the Business Location Choice Model (BLCM), we predict the probability that an establishment that is either new (from the Business Transition model), or has moved within the region (Business Relocation model), will be located at a particular employment submarket location. Employment submarkets are defined as jurisdiction, building type, and transit-proximity combinations.

The BLCM is specified as a multinomial logit (MNL) model, with separate equations estimated for each employment sector. An MNL is applied to estimate the probability that each establishment will move to each of the alternative employment submarkets under consideration. Monte Carlo simulation is used to generate a decision to locate in a particular employment submarket. Once this choice is made, the establishment is assigned to the employment submarket. In the next step, establishments are assigned to specific parcel-level buildings within the employment submarket using a simple location choice model that accounts for available job spaces within buildings. Business Location Choice Model coefficients are presented in Table 4.26.

The number of job spots available in an employment submarket that establishments can locate in will depend mainly on the total square footage of non-residential floorspace in the employment submarket, and on the square feet per employee in the building type that the employment submarket represents (for each building type, a certain number of square feet are defined as the minimum to support each job).

BLCM estimation has been performed for all sectors except government. In the base-year, existing establishments were assigned to buildings. The BLCM is comprised of a number of submodels, one for each modeled employment sector. In simulation, the BLCM is run after the Business Transition and Business Relocation models. Establishment choice of employment submarket is simulated by submodel, and once all establishments have selected an employment submarket with capacity, they are allocated to specific buildings with capacity within the employment submarket. Each submodel was specified independently. The variable sets were somewhat similar across submodels although there is quite a bit of variation owing to the principal that establishments in different sectors predicate their location choices on different factors. It is hypothesized that establishment choice of location is positively associated with accessibility, negatively associated with price, and positively associated with non-residential square footage. For certain employment sector submodels, a positive association with transit-presence and jobs of the same sector is hypothesized. The relationship between establishments and buildings of a certain type (such as office structures), and between establishments and population, is hypothesized to vary by employment sector.

Table 4.26: Business Location Choice Model Coefficients

Submodel	Coefficient Name	Estimate	Standard Error	T-Statistic
1	esubmarket_alameda_county	-0.5	1	2
1	esubmarket_avg_transit_peak_total_access	0.06888	0.0075	9.18387
1	esubmarket_close_to_transit	0.37604	0.02723	13.80737
1	esubmarket_contracosta_county	2	1	2
1	esubmarket_marin_county	4.25	1	2
1	esubmarket_napa_county	4	1	2
1	esubmarket_sanfrancisco_county	-1.5	1	2
1	esubmarket_sanmateo_county	0.5	1	2
1	esubmarket_solano_county	9	1	2
1	esubmarket_sonoma_county	2	1	2
1	is_office_esubmarket	1.80169	0.03094	58.23391
1	ln_avg_nonres_rent	-0.18019	0.02214	-8.1398
1	ln_jobs_in_jurisdiction	0.12346	0.01799	6.86468
1	ln_non_residential_sqft_esubmarket	0.71928	0.01281	56.1528
1	share_jobs_sector_1	1.38197	0.34387	4.01891
2	esubmarket_alameda_county	-0.5	1	2
2	esubmarket_avg_transit_peak_total_access	0.02033	0.00505	4.026
2	esubmarket_close_to_transit	0.28286	0.01935	14.61472
2	esubmarket_contracosta_county	2	1	2
2	esubmarket_marin_county	4.25	1	2
2	esubmarket_napa_county	4	1	2
2	esubmarket_sanfrancisco_county	0	1	2
2	esubmarket_sanmateo_county	0.5	1	2
2	esubmarket_solano_county	9	1	2
2	esubmarket_sonoma_county	2	1	2
2	is_office_esubmarket	1.48979	0.02046	72.79925
2	ln_avg_nonres_rent	-0.07567	0.01366	-5.53944
2	ln_jobs_in_jurisdiction	0.13448	0.01191	11.28626
2	ln_non_residential_sqft_esubmarket	0.64677	0.00884	73.19049
2	share_jobs_sector_2	2.55412	0.17917	14.2556
3	esubmarket_alameda_county	-0.5	1	2
3	esubmarket_avg_transit_peak_total_access	0.05642	0.00506	11.14619
3	esubmarket_close_to_transit	0.24574	0.01866	13.17
3	esubmarket_contracosta_county	2	1	2
3	esubmarket_marin_county	4.25	1	2
3	esubmarket_napa_county	4	1	2
3	esubmarket_sanfrancisco_county	-1.5	1	2
3	esubmarket_sanmateo_county	0.5	1	2
3	esubmarket_solano_county	9	1	2
3	esubmarket_sonoma_county	2	1	2
3	is_office_esubmarket	1.01057	0.01985	50.91223
3	ln_avg_nonres_rent	-0.19507	0.01296	-15.05483
3	ln_jobs_in_jurisdiction	0.15184	0.01178	12.88719
3	ln_non_residential_sqft_esubmarket	0.68213	0.00845	80.73724
3	share_jobs_sector_3	2.69226	0.19889	13.53641
4	esubmarket_alameda_county	-0.5	1	2
4	esubmarket_avg_transit_peak_total_access	-0.0829	0.01849	-4.48312
4	esubmarket_close_to_transit	0.0527	0.0746	0.70642
4	esubmarket_contracosta_county	2	1	2
4	esubmarket_marin_county	4.25	1	2

4	esubmarket_napa_county	4	1	2
4	esubmarket_sanfrancisco_county	-1.5	1	2
4	esubmarket_sanmateo_county	0.5	1	2
4	esubmarket_solano_county	9	1	2
4	esubmarket_sonoma_county	2	1	2
4	is_office_esubmarket	0.35256	0.07998	4.40786
4	ln_avg_nonres_rent	-0.9	0.04826	1.70529
4	ln_jobs_in_jurisdiction	-0.05427	0.04545	-1.19398
4	ln_non_residential_sqft_esubmarket	0.70192	0.03311	21.19945
4	share_jobs_sector_4	0.30102	1.8728	0.16073
5	esubmarket_alameda_county	-0.5	1	2
5	esubmarket_avg_transit_peak_total_access	-0.20324	0.06381	-3.18521
5	esubmarket_close_to_transit	0.73177	0.32327	2.26361
5	esubmarket_contracosta_county	2	1	2
5	esubmarket_marin_county	4.25	1	2
5	esubmarket_napa_county	4	1	2
5	esubmarket_sanfrancisco_county	-1.5	1	2
5	esubmarket_sanmateo_county	0.5	1	2
5	esubmarket_solano_county	9	1	2
5	esubmarket_sonoma_county	2	1	2
5	is_office_esubmarket	1.52251	0.35	4.35003
5	ln_avg_nonres_rent	-1.61574	0.18137	-8.90856
5	ln_jobs_in_jurisdiction	0.47996	0.16189	2.96471
5	ln_non_residential_sqft_esubmarket	0.68149	0.1302	5.23399
5	share_jobs_sector_5	6.97405	2.53257	2.75375
6	esubmarket_alameda_county	-0.5	1	2
6	esubmarket_avg_transit_peak_total_access	0.07209	0.0119	6.06076
6	esubmarket_close_to_transit	0.46052	0.0481	9.57457
6	esubmarket_contracosta_county	2	1	2
6	esubmarket_marin_county	4.25	1	2
6	esubmarket_napa_county	4	1	2
6	esubmarket_sanfrancisco_county	-1.5	1	2
6	esubmarket_sanmateo_county	0.5	1	2
6	esubmarket_solano_county	9	1	2
6	esubmarket_sonoma_county	2	1	2
6	is_office_esubmarket	0.01927	0.05539	0.34787
6	ln_avg_nonres_rent	-0.09591	0.02745	-3.49367
6	ln_jobs_in_jurisdiction	0.06527	0.02878	2.2678
6	ln_non_residential_sqft_esubmarket	0.62613	0.02111	29.65766
6	share_jobs_sector_6	2.09311	0.63675	3.2872
7	esubmarket_alameda_county	-0.5	1	2
7	esubmarket_avg_transit_peak_total_access	0.10523	0.02669	3.94319
7	esubmarket_close_to_transit	0.37421	0.09902	3.77903
7	esubmarket_contracosta_county	2	1	2
7	esubmarket_marin_county	4.25	1	2
7	esubmarket_napa_county	4	1	2
7	esubmarket_sanfrancisco_county	-1.5	1	2
7	esubmarket_sanmateo_county	0.5	1	2
7	esubmarket_solano_county	9	1	2
7	esubmarket_sonoma_county	2	1	2
7	is_office_esubmarket	1.91125	0.11315	16.89071
7	ln_avg_nonres_rent	-1.7925	0.05872	-30.52776
7	ln_jobs_in_jurisdiction	0.28983	0.06083	4.76451
7	ln_non_residential_sqft_esubmarket	0.51724	0.04694	11.01985

7	share_jobs_sector_7	5.78703	0.64838	8.92529
8	esubmarket_alameda_county	-0.5	1	2
8	esubmarket_avg_transit_peak_total_access	0.1258	0.02088	6.02554
8	esubmarket_close_to_transit	0.1935	0.0788	2.45545
8	esubmarket_contracosta_county	2	1	2
8	esubmarket_marin_county	4.25	1	2
8	esubmarket_napa_county	4	1	2
8	esubmarket_sanfrancisco_county	-1.5	1	2
8	esubmarket_sanmateo_county	0.5	1	2
8	esubmarket_solano_county	9	1	2
8	esubmarket_sonoma_county	2	1	2
8	is_office_esubmarket	1.18873	0.08112	14.6547
8	ln_avg_nonres_rent	-0.66606	0.04804	-13.86421
8	ln_jobs_in_jurisdiction	0.09967	0.04983	2.00045
8	ln_non_residential_sqft_esubmarket	0.61618	0.03553	17.34465
8	share_jobs_sector_8	1.05183	5.52571	0.19035
9	esubmarket_alameda_county	-0.5	1	2
9	esubmarket_avg_transit_peak_total_access	0.06197	0.00783	7.91373
9	esubmarket_close_to_transit	0.41182	0.03014	13.66159
9	esubmarket_contracosta_county	2	1	2
9	esubmarket_marin_county	4.25	1	2
9	esubmarket_napa_county	4	1	2
9	esubmarket_sanfrancisco_county	-1.5	1	2
9	esubmarket_sanmateo_county	0.5	1	2
9	esubmarket_solano_county	9	1	2
9	esubmarket_sonoma_county	2	1	2
9	is_office_esubmarket	-0.69203	0.04007	-17.26847
9	ln_avg_nonres_rent	-0.9	0.01713	4.20567
9	ln_jobs_in_jurisdiction	0.09057	0.01892	4.78602
9	ln_non_residential_sqft_esubmarket	0.65221	0.01347	48.42725
9	share_jobs_sector_9	1.97623	0.38107	5.18599
10	esubmarket_alameda_county	-0.5	1	2
10	esubmarket_avg_transit_peak_total_access	0.07304	0.0086	8.49246
10	esubmarket_close_to_transit	0.48235	0.03221	14.97552
10	esubmarket_contracosta_county	2	1	2
10	esubmarket_marin_county	4.25	1	2
10	esubmarket_napa_county	4	1	2
10	esubmarket_sanfrancisco_county	-1.5	1	2
10	esubmarket_sanmateo_county	0.5	1	2
10	esubmarket_solano_county	9	1	2
10	esubmarket_sonoma_county	2	1	2
10	is_office_esubmarket	-1.29264	0.04638	-27.86878
10	ln_avg_nonres_rent	-0.9	0.01892	37.17438
10	ln_jobs_in_jurisdiction	-0.02215	0.02239	-0.98926
10	ln_non_residential_sqft_esubmarket	0.74465	0.01473	50.56183
10	share_jobs_sector_10	1.92532	0.43434	4.43274
11	esubmarket_alameda_county	-0.5	1	2
11	esubmarket_avg_transit_peak_total_access	0.00678	0.0064	1.05917
11	esubmarket_close_to_transit	0.11513	0.02473	4.65474
11	esubmarket_contracosta_county	2	1	2
11	esubmarket_marin_county	4.25	1	2
11	esubmarket_napa_county	4	1	2
11	esubmarket_sanfrancisco_county	-1.5	1	2
11	esubmarket_sanmateo_county	0.5	1	2

11	esubmarket_solano_county	9	1	2
11	esubmarket_sonoma_county	2	1	2
11	is_office_esubmarket	0.22015	0.03065	7.18211
11	ln_avg_nonres_rent	-1.00923	0.0198	-50.98092
11	ln_jobs_in_jurisdiction	0.1665	0.01609	10.34551
11	ln_non_residential_sqft_esubmarket	0.77109	0.01191	64.74244
11	share_jobs_sector_11	-2.37074	0.27102	-8.74751
12	esubmarket_alameda_county	-0.5	1	2
12	esubmarket_avg_transit_peak_total_access	-0.0107	0.03008	-0.35564
12	esubmarket_close_to_transit	0.34274	0.11371	3.01413
12	esubmarket_contracosta_county	2	1	2
12	esubmarket_marin_county	4.25	1	2
12	esubmarket_napa_county	4	1	2
12	esubmarket_sanfrancisco_county	-1.5	1	2
12	esubmarket_sanmateo_county	0.5	1	2
12	esubmarket_solano_county	9	1	2
12	esubmarket_sonoma_county	2	1	2
12	is_office_esubmarket	0.44598	0.13482	3.30799
12	ln_avg_nonres_rent	-1.03179	0.07881	-13.09218
12	ln_jobs_in_jurisdiction	0.22622	0.07759	2.91554
12	ln_non_residential_sqft_esubmarket	0.71273	0.05657	12.59965
12	share_jobs_sector_12	2.2656	13.15677	0.1722
13	esubmarket_alameda_county	-0.5	1	2
13	esubmarket_avg_transit_peak_total_access	-0.15146	0.01497	-10.11522
13	esubmarket_close_to_transit	-0.08492	0.04563	-1.86095
13	esubmarket_contracosta_county	2	1	2
13	esubmarket_ln_residential_units_within_walking_distance	1.00969	0.04007	25.19856
13	esubmarket_marin_county	4.25	1	2
13	esubmarket_napa_county	4	1	2
13	esubmarket_sanfrancisco_county	-1.5	1	2
13	esubmarket_sanmateo_county	0.5	1	2
13	esubmarket_solano_county	9	1	2
13	esubmarket_sonoma_county	2	1	2
13	is_office_esubmarket	1.77063	0.0478	37.04317
13	ln_avg_nonres_rent	-1.46442	0.03078	-47.57436
13	ln_jobs_in_jurisdiction	0.20599	0.02934	7.02134
13	ln_non_residential_sqft_esubmarket	0.53124	0.02213	24.0027
13	share_jobs_sector_13	3.48378	0.69004	5.04863
14	esubmarket_alameda_county	-0.5	1	2
14	esubmarket_avg_auto_peak_total_access	0.10014	0.03877	2.58265
14	esubmarket_close_to_transit	0.04907	0.04952	0.99086
14	esubmarket_contracosta_county	2	1	2
14	esubmarket_marin_county	4.25	1	2
14	esubmarket_napa_county	4	1	2
14	esubmarket_sanfrancisco_county	-1.5	1	2
14	esubmarket_sanmateo_county	0.5	1	2
14	esubmarket_solano_county	9	1	2
14	esubmarket_sonoma_county	2	1	2
14	is_office_esubmarket	-0.38323	0.0769	-4.9838
14	ln_avg_nonres_rent	-1.35652	0.04464	-30.38671
14	ln_jobs_in_jurisdiction	0.05522	0.03202	1.72464
14	ln_non_residential_sqft_esubmarket	0.8338	0.02415	34.52124
14	share_jobs_sector_14	0.97855	0.55562	1.76119
15	esubmarket_alameda_county	-0.5	1	2

15	esubmarket_avg_transit_peak_total_access	-0.12417	0.00678	-18.32435
15	esubmarket_close_to_transit	0.02941	0.02305	1.27579
15	esubmarket_contracosta_county	2	1	2
15	esubmarket_ln_residential_units_within_walking_distance	0.73493	0.01585	46.3702
15	esubmarket_marin_county	4.25	1	2
15	esubmarket_napa_county	4	1	2
15	esubmarket_sanfrancisco_county	-1.5	1	2
15	esubmarket_sanmateo_county	0.5	1	2
15	esubmarket_solano_county	9	1	2
15	esubmarket_sonoma_county	2	1	2
15	is_office_esubmarket	-1.1818	0.02982	-39.63638
15	ln_avg_nonres_rent	-0.13605	0.01422	-9.56999
15	ln_jobs_in_jurisdiction	-0.04234	0.01493	-2.83641
15	ln_non_residential_sqft_esubmarket	0.77738	0.01026	75.79861
15	share_jobs_sector_15	1.71442	0.30518	5.61769
16	esubmarket_alameda_county	-0.5	1	2
16	esubmarket_avg_transit_peak_total_access	-0.07139	0.00787	-9.06892
16	esubmarket_close_to_transit	0.06752	0.02407	2.80557
16	esubmarket_contracosta_county	2	1	2
16	esubmarket_ln_residential_units_within_walking_distance	0.58481	0.02073	28.20799
16	esubmarket_marin_county	4.25	1	2
16	esubmarket_napa_county	4	1	2
16	esubmarket_sanfrancisco_county	-1.5	1	2
16	esubmarket_sanmateo_county	0.5	1	2
16	esubmarket_solano_county	9	1	2
16	esubmarket_sonoma_county	2	1	2
16	is_office_esubmarket	1.94611	0.02659	73.19583
16	ln_avg_nonres_rent	-0.45364	0.01764	-25.7235
16	ln_jobs_in_jurisdiction	0.15905	0.01606	9.90073
16	ln_non_residential_sqft_esubmarket	0.61377	0.01186	51.76307
16	share_jobs_sector_16	3.22152	0.21333	15.10137
17	esubmarket_alameda_county	-0.5	1	2
17	esubmarket_avg_auto_peak_total_access	0.36456	0.05002	7.28789
17	esubmarket_close_to_transit	-0.10622	0.0609	-1.74408
17	esubmarket_contracosta_county	2	1	2
17	esubmarket_ln_residential_units_within_walking_distance	0.30333	0.03127	9.69923
17	esubmarket_marin_county	4.25	1	2
17	esubmarket_napa_county	4	1	2
17	esubmarket_sanfrancisco_county	-1.5	1	2
17	esubmarket_sanmateo_county	0.5	1	2
17	esubmarket_solano_county	9	1	2
17	esubmarket_sonoma_county	2	1	2
17	is_office_esubmarket	0.63358	0.06109	10.37122
17	ln_avg_nonres_rent	-0.75187	0.04162	-18.06489
17	ln_jobs_in_jurisdiction	0.02892	0.03559	0.81261
17	ln_non_residential_sqft_esubmarket	0.66982	0.02605	25.71649
17	share_jobs_sector_17	5.07757	0.55343	9.17474
18	esubmarket_alameda_county	-0.5	1	2
18	esubmarket_avg_transit_peak_total_access	-0.21574	0.10766	-2.00382
18	esubmarket_close_to_transit	-0.53799	0.33432	-1.60922
18	esubmarket_contracosta_county	2	1	2
18	esubmarket_ln_residential_units_within_walking_distance	1.34981	0.27339	4.93734
18	esubmarket_marin_county	4.25	1	2
18	esubmarket_napa_county	4	1	2

18	esubmarket_sanfrancisco_county	-1.5	1	2
18	esubmarket_sanmateo_county	0.5	1	2
18	esubmarket_solano_county	9	1	2
18	esubmarket_sonoma_county	2	1	2
18	is_office_esubmarket	1.59352	0.27912	5.70903
18	ln_avg_nonres_rent	-2.27596	0.21961	-10.36371
18	ln_jobs_in_jurisdiction	0.61951	0.18557	3.33841
18	ln_non_residential_sqft_esubmarket	0.56889	0.15253	3.72967
18	share_jobs_sector_18	11.38959	1.82986	6.22429
19	esubmarket_alameda_county	-0.5	1	2
19	esubmarket_avg_auto_peak_total_access	-0.18859	0.10039	-1.87857
19	esubmarket_close_to_transit	0.14666	0.12413	1.18153
19	esubmarket_contracosta_county	2	1	2
19	esubmarket_ln_residential_units_within_walking_distance	0.31742	0.06911	4.59295
19	esubmarket_marin_county	4.25	1	2
19	esubmarket_napa_county	4	1	2
19	esubmarket_sanfrancisco_county	-1.5	1	2
19	esubmarket_sanmateo_county	0.5	1	2
19	esubmarket_solano_county	9	1	2
19	esubmarket_sonoma_county	2	1	2
19	is_office_esubmarket	1.03137	0.12546	8.22088
19	ln_avg_nonres_rent	-1.68234	0.09375	-17.94453
19	ln_jobs_in_jurisdiction	0.23593	0.07482	3.15326
19	ln_non_residential_sqft_esubmarket	0.72809	0.05324	13.67654
19	share_jobs_sector_19	2.39901	6.84219	0.35062
20	esubmarket_alameda_county	-0.5	1	2
20	esubmarket_avg_auto_peak_total_access	-0.02755	0.02656	-1.03722
20	esubmarket_close_to_transit	-0.1013	0.0335	-3.02362
20	esubmarket_contracosta_county	2	1	2
20	esubmarket_ln_residential_units_within_walking_distance	0.25967	0.01839	14.12365
20	esubmarket_marin_county	4.25	1	2
20	esubmarket_napa_county	4	1	2
20	esubmarket_sanfrancisco_county	-1.5	1	2
20	esubmarket_sanmateo_county	0.5	1	2
20	esubmarket_solano_county	9	1	2
20	esubmarket_sonoma_county	2	1	2
20	is_office_esubmarket	0.33675	0.03797	8.86866
20	ln_avg_nonres_rent	-1.1891	0.02414	-49.26128
20	ln_jobs_in_jurisdiction	0.11749	0.01934	6.07603
20	ln_non_residential_sqft_esubmarket	0.65141	0.01474	44.19037
20	share_jobs_sector_20	3.10188	0.38667	8.02193
21	esubmarket_alameda_county	-0.5	1	2
21	esubmarket_avg_transit_peak_total_access	-0.12336	0.06334	-1.94748
21	esubmarket_close_to_transit	-0.56687	0.21655	-2.61778
21	esubmarket_contracosta_county	2	1	2
21	esubmarket_ln_residential_units_within_walking_distance	0.00029	0.12876	0.00225
21	esubmarket_marin_county	4.25	1	2
21	esubmarket_napa_county	4	1	2
21	esubmarket_sanfrancisco_county	-1.5	1	2
21	esubmarket_sanmateo_county	0.5	1	2
21	esubmarket_solano_county	9	1	2
21	esubmarket_sonoma_county	2	1	2
21	is_office_esubmarket	0.54696	0.23634	2.31435
21	ln_avg_nonres_rent	-0.2334	0.17513	-1.33271

21	ln_jobs_in_jurisdiction	0.27907	0.13272	2.10266
21	ln_non_residential_sqft_esubmarket	0.75892	0.09232	8.22058
21	share_jobs_sector_21	5.43973	2.03179	2.67731
22	esubmarket_alameda_county	-0.5	1	2
22	esubmarket_avg_auto_peak_total_access	-0.21566	0.03494	-6.1719
22	esubmarket_close_to_transit	0.0122	0.05077	0.24024
22	esubmarket_contracosta_county	2	1	2
22	esubmarket_ln_residential_units_within_walking_distance	0.25667	0.02564	10.00958
22	esubmarket_marin_county	4.25	1	2
22	esubmarket_napa_county	4	1	2
22	esubmarket_sanfrancisco_county	-1.5	1	2
22	esubmarket_sanmateo_county	0.5	1	2
22	esubmarket_solano_county	9	1	2
22	esubmarket_sonoma_county	2	1	2
22	is_office_esubmarket	-0.28082	0.05847	-4.80287
22	ln_avg_nonres_rent	-0.88059	0.03543	-24.852
22	ln_jobs_in_jurisdiction	0.11826	0.02858	4.13736
22	ln_non_residential_sqft_esubmarket	0.78375	0.02151	36.43852
22	share_jobs_sector_22	1.86882	0.53049	3.52283
23	esubmarket_alameda_county	-0.5	1	2
23	esubmarket_avg_transit_peak_total_access	0.00983	0.00912	1.07743
23	esubmarket_close_to_transit	0.02686	0.0302	0.88962
23	esubmarket_contracosta_county	2	1	2
23	esubmarket_ln_residential_units_within_walking_distance	0.21491	0.02018	10.64815
23	esubmarket_marin_county	4.25	1	2
23	esubmarket_napa_county	4	1	2
23	esubmarket_sanfrancisco_county	-1.5	1	2
23	esubmarket_sanmateo_county	0.5	1	2
23	esubmarket_solano_county	9	1	2
23	esubmarket_sonoma_county	2	1	2
23	is_office_esubmarket	0.93931	0.03025	31.0533
23	ln_avg_nonres_rent	-0.29168	0.02249	-12.96652
23	ln_jobs_in_jurisdiction	0.11947	0.01753	6.81516
23	ln_non_residential_sqft_esubmarket	0.76301	0.01274	59.90509
23	share_jobs_sector_23	2.55666	0.16136	15.8446
24	esubmarket_alameda_county	-0.5	1	2
24	esubmarket_avg_transit_peak_total_access	-0.09569	0.02974	-3.2175
24	esubmarket_close_to_transit	-0.0018	0.10123	-0.01774
24	esubmarket_contracosta_county	2	1	2
24	esubmarket_ln_residential_units_within_walking_distance	1.17499	0.04727	24.85765
24	esubmarket_marin_county	4.25	1	2
24	esubmarket_napa_county	4	1	2
24	esubmarket_sanfrancisco_county	-1.5	1	2
24	esubmarket_sanmateo_county	0.5	1	2
24	esubmarket_solano_county	9	1	2
24	esubmarket_sonoma_county	2	1	2
24	is_office_esubmarket	-0.00506	0.12444	-0.04067
24	ln_avg_nonres_rent	-2.15137	0.05542	-38.81776
24	ln_jobs_in_jurisdiction	0.38074	0.06329	6.01538
24	ln_non_residential_sqft_esubmarket	0.41021	0.04513	9.08978
24	share_jobs_sector_24	7.81124	1.34781	5.79549
25	esubmarket_alameda_county	-0.5	1	2
25	esubmarket_avg_transit_peak_total_access	-0.04402	0.02045	-2.15293
25	esubmarket_close_to_transit	-0.15599	0.06801	-2.29372

25	esubmarket_contracosta_county	2	1	2
25	esubmarket_ln_residential_units_within_walking_distance	-0.06687	0.04275	-1.56393
25	esubmarket_marin_county	4.25	1	2
25	esubmarket_napa_county	4	1	2
25	esubmarket_sanfrancisco_county	-1.5	1	2
25	esubmarket_sanmateo_county	0.5	1	2
25	esubmarket_solano_county	9	1	2
25	esubmarket_sonoma_county	2	1	2
25	is_office_esubmarket	0.46005	0.07878	5.83939
25	ln_avg_nonres_rent	-0.753	0.06191	-12.16313
25	ln_jobs_in_jurisdiction	0.18191	0.04141	4.39248
25	ln_non_residential_sqft_esubmarket	0.86535	0.03143	27.52868
25	share_jobs_sector_25	5.00899	0.31616	15.84301
26	esubmarket_alameda_county	-0.5	1	2
26	esubmarket_avg_transit_peak_total_access	-0.11462	0.00585	-19.60752
26	esubmarket_close_to_transit	-0.05415	0.01858	-2.91344
26	esubmarket_contracosta_county	2	1	2
26	esubmarket_ln_residential_units_within_walking_distance	0.78187	0.01389	56.30621
26	esubmarket_marin_county	4.25	1	2
26	esubmarket_napa_county	4	1	2
26	esubmarket_sanfrancisco_county	-1.5	1	2
26	esubmarket_sanmateo_county	0.5	1	2
26	esubmarket_solano_county	9	1	2
26	esubmarket_sonoma_county	2	1	2
26	is_office_esubmarket	-0.03034	0.0192	-1.5798
26	ln_avg_nonres_rent	-0.62622	0.01211	-51.71799
26	ln_jobs_in_jurisdiction	0.02014	0.01175	1.71317
26	ln_non_residential_sqft_esubmarket	0.70226	0.00853	82.29686
26	share_jobs_sector_26	1.85266	0.35884	5.16286
27	esubmarket_alameda_county	-0.5	1	2
27	esubmarket_avg_transit_peak_total_access	-0.04276	0.04329	-0.98763
27	esubmarket_close_to_transit	-0.10852	0.1223	-0.88734
27	esubmarket_contracosta_county	2	1	2
27	esubmarket_ln_residential_units_within_walking_distance	0.55815	0.08808	6.33673
27	esubmarket_marin_county	4.25	1	2
27	esubmarket_napa_county	4	1	2
27	esubmarket_sanfrancisco_county	-1.5	1	2
27	esubmarket_sanmateo_county	0.5	1	2
27	esubmarket_solano_county	9	1	2
27	esubmarket_sonoma_county	2	1	2
27	is_office_esubmarket	0.99206	0.13823	7.17691
27	ln_avg_nonres_rent	-0.6898	0.08722	-7.90839
27	ln_jobs_in_jurisdiction	-0.04111	0.06716	-0.61221
27	ln_non_residential_sqft_esubmarket	0.7584	0.02656	28.55598
27	share_jobs_sector_27	384.07703	0.65131	589.69714
28	esubmarket_alameda_county	-0.5	1	2
28	esubmarket_avg_transit_peak_total_access	-0.2373	0.05092	-4.65995
28	esubmarket_close_to_transit	-0.42556	0.15256	-2.78941
28	esubmarket_contracosta_county	2	1	2
28	esubmarket_ln_residential_units_within_walking_distance	1.31053	0.14789	8.86125
28	esubmarket_marin_county	4.25	1	2
28	esubmarket_napa_county	4	1	2
28	esubmarket_sanfrancisco_county	-1.5	1	2
28	esubmarket_sanmateo_county	0.5	1	2

28	esubmarket_solano_county	9	1	2
28	esubmarket_sonoma_county	2	1	2
28	is_office_esubmarket	1.88894	0.15419	12.25043
28	ln_avg_nonres_rent	-2.75949	0.11578	-23.83475
28	ln_jobs_in_jurisdiction	0.44782	0.10402	4.30511
28	ln_non_residential_sqft_esubmarket	0.42823	0.07966	5.3756
28	share_jobs_sector_28	6.95702	2.99011	2.32668

4.3 Real Estate Price Model

The Real Estate Price Model (REPM) is an Ordinary Least Squares (OLS) regression model that predicts the price of residential units and non-residential square footage. UrbanSim uses prices as the indicator of the match between demand and supply of various development types, and of the relative market valuations for attributes of housing, nonresidential space, and location. Since prices enter the location choice utility functions for most BLCM and HLCM submodels, an adjustment in prices will alter location preferences. Similarly, an adjustment in price influences the project location decisions of developers.

Prices are modeled using a hedonic regression of unit value on attributes of the building and its environment. The unit whose value is being modeled is either a residential unit or a non-residential square foot. For residential buildings, the dependent variable is the natural log of the price per residential unit or rent per residential unit (depending on tenure). Price per residential unit is the building improvement value divided by the total number of residential units in the building. Rent per residential units is based on predicted rents based on a regression equation estimated off of Costar data. In the case of single-family detached buildings, the unit price equals the building improvement value. Separate regressions are run for each residential building type. For non-residential buildings, the dependent value is the natural log of the rent per nonresidential square-foot. Separate regressions are run for each non-residential building type. Explanatory variables in the price models include building type dummies, accessibility, household income, number of stories, building age (whether or not build before 1930), and residential unit square footage. Prices are hypothesized to be positively associated with income, accessibility, stories, and square footage. Being built before 1930 (historic structures) is also hypothesized to exhibit a positive relationship with price.

The REPM updates the unit price attributes in the building table or the residential_units table. Instead of storing price as the natural log of price (this is what is actually estimated and predicted), the REPM automatically exponentiates the predicted value so that the unit prices stored in the tables are more understandable. The REPM models run near the beginning of each simulation year; prices are updated in the simulation in the following order: non-residential rent, residential rent, residential sale price. Real Estate Price Model coefficients are presented in Tables 4.27, 4.28, and 4.28.

The hedonic regression is estimated off of the the base-year buildings and residential_units tables, which are assembled from assessor records and supplemented with additional price data such as Costar. Explanatory variables include measures of accessibility, real estate characteristics, proximity to amenities. The hedonic regression equation encapsulates interactions between market demand and supply, revealing an envelope of implicit valuations. Because the hedonic regression includes variables that are maintained as part of the simulation system, these are used to update relative prices during simulation. Prices are updated annually at the beginning of the simulation year and also during an equilibration step following simulation of the demand models.

Table 4.27: Non-Residential Units - Rent Model Coefficients

Coefficient Name	Estimate	Standard Error	T-Statistic
bdlg_in_san_francisco	0.11615	0.02514	4.61945
bdlg_type_hotel	0.51298	0.07712	6.6514
bdlg_type_mixed_use	0.73969	0.02789	26.52508
bdlg_type_office	0.70843	0.01552	45.63552
bdlg_type_strip_mall	0.74473	0.01701	43.76937
bldg_avg_auto_peak_total_access	0.07512	0.00921	8.15595
bldg_ln_average_income_within_500_meters	0.02049	0.00216	9.5065
bdlg_office_x_san_francisco	1.5	1	1
stories	0.01441	0.00217	6.63596
constant	1.17445	0.1125	10.43933

Table 4.28: Residential Units - Sale Price Model Coefficients

Coefficient Name	Estimate	Standard Error	T-Statistic
built_pre_1930	0.11892	0.00497	23.94785
ln_average_income_within_500_meters	0.54556	0.00261	209.00764
ln_lot_sqft	0.22366	0.00178	125.4635
ln_unit_sqft	0.0106	0.00104	10.16333
transit_peak_total_access	0.0081	0.00055	14.84213
transit_within_half_mile	0.25349	0.01046	24.2412
unit_is_single_family	-0.46518	0.00581	-80.05428
constant	6.32411	0.0271	233.34106

Table 4.29: Residential Units - Rent Model Coefficients

Coefficient Name	Estimate	Standard Error	T-Statistic
built_pre_1930	0.05948	0.00508	11.70141
ln_average_income_within_500_meters	-0.00362	0.00026	-13.99987
ln_unit_sqft	0.74352	0.00202	367.38391
transit_peak_total_access	0.04391	0.00018	241.54031
transit_within_half_mile	0.16645	0.0019	87.80073
constant	2.14473	0.01382	155.19301

4.4 Calibration, Validation, and Sensitivity Analyses

This section describes calibration, validation, and sensitivity testing of the Bay Area UrbanSim model. To evaluate the empirical validity of the models, the 1-year period from 2010 to 2011 was simulated, and predictions were compared to validation targets that assumed the continuation of recently-observed spatial patterns of growth in households, residential units, employment, and non-residential space. Sensitivity testing involved running the model out to 2040 and assessing the model with respect to appropriate policy sensitivities. These exercises provide information on the forecasting capability of the models. Validation was undertaken at a number of geographic levels, but the county level was the focus.

Because the base-year is 2010, simulation results reflect predictions for year 2011 and beyond, for which there was relatively little observed data. ABAG prepared 2011 household, employment, residential unit, and built-space targets that were used in calibration. These targets were created based on recently observed growth and development patterns and informed by local expertise on development pressures and constraints in the Bay Area. The goal was to create targets that reflected an extrapolation to 2011 based on normal patterns of growth during a healthy economy. A focus was getting good measures of the inter-county distribution of growth. Creating targets based on longer, more mixed period was seen as valuable, since the end of the last decade included a historically sharp recession. For example, the 2011 employment targets that were calculated using 2008-2010 data implied a decline in employment for some counties. 2011 targets calculated based on pre-recession data seemed quite a bit more reasonable to calibrate to, given that negative growth rates over the entire forecast period is unlikely. Calibrating to historical trends (even if only recent trends are considered) should not be the only determining factor in a land use forecast. Fortunately, UrbanSim accounts for a wide variety of variables that will influence growth separate from the calibration process. For example, counties that have historically grown very rapidly can run out of zoned capacity, shifting growth to counties that historically experienced slower growth. Congestion effects and price effects can influence the spatial distribution of growth in the simulation. These are examples of complex feedback effects that UrbanSim is designed to handle.

The 2011 household and employment targets by county were used as calibration and validation targets for the household location choice model and employment location choice model. Calibration of the demand-side models consisted primarily of adding county dummy variables to the specification and adjusting coefficient values for these dummy variables. An iterative process of running 1-year simulations, comparing output to targets, and then adjusting county dummy coefficients to try and better match targets was the main approach to calibration of the demand-side models. Since all the models interact with each other, each result reflects the intricate interplay of multiple UrbanSim components. When adjusting one model component as part of the calibration process, results from other components would often change, so an iterative and time-consuming process was needed.

The 2011 residential unit and non-residential space targets by county and building type were used as calibration and validation targets for the real estate developer model. Accounting for the fact that the end of the last decade was a highly irregular and recessionary period, built space targets were prepared multiple ways- using longer periods where irregularities tend to average out and also using shorter fast-growth periods that reflect a healthy economy. Using faster periods of growth had the added advantage that certain rarer development types didn't drop out of the calibration targets. Extensive testing, adjustment, and calibration of the developer model were undertaken based on these targets. Cost shifters (county-level factors used to shift real estate development costs up or down), price shifters, and assumptions such as the proportion of parcels to consider for development each year were adjusted in the calibration process. These adjustments helped move development patterns (in terms of residential units and non-residential square footage by building type) towards the pattern suggested by the targets.

The second step after validation/calibration was sensitivity testing. The model was repeatedly run out to 2040, and simulation results were gauged with respect to their having the appropriate policy sensitivities. Runs were compared with respect to development outcomes, the spatial distribution of households and employment, expected differences between counties, PDA-nonPDA shares, and the expected effect of policy initiatives (policies vary by scenario). Adjustments were then made, followed by additional runs. This process of testing helped to assess reasonableness of simulation output and sensitivity to policies of interest, as well as providing guidance as to how to better calibrate the model. Adjustments made as a result of the sensitivity testing included:

- Updating parcel subsidies (for scenarios where such subsidies were used to represent certain policies) based on the simulation results to ensure that differences in development patterns between policy-based scenarios were reasonable. Differences in simulated spatial patterns between runs should reflect differences in policy content between scenarios.

- Adjustments aimed to ensure that simulation results had the proper sensitivity to PDA-oriented policies. For example, in some scenarios we would expect more construction occurring in the PDAs due to policies that would make PDAs substantially more attractive to real estate development. Simulation results should reflect this policy sensitivity.
- Additional calibration to achieve a closer correspondence between simulated and target amounts of growth by county and PDA. 2040 growth targets from ABAG represent substantial local knowledge and expertise, so moving UrbanSim results closer to these was a desirable goal.
- Monitoring the number of unplaced households in out-years, which is a sign of simulated imbalance between demand and supply, and making model configuration changes to reduce the number.

Sensitivity testing facilitated the evaluation of full model results for plausibility and the extent to which expected policy effects were seen. Where appropriate policy sensitivities were not present, model adjustments were made, followed by additional test runs. This exercise was a useful exploration of the model's responsiveness and provided information on the trade-offs that might be involved in implementing alternative scenarios.

CHAPTER

FIVE

Software Platform

5.1 The Open Platform for Urban Simulation

UrbanSim has been implemented in an open source software platform called the Open Platform for Urban Simulation (OPUS). This section provides an overview of OPUS, beginning with a quick review of its key features.

5.1.1 Graphical User Interface

A flexible, cross-platform user interface has been implemented for OPUS that organizes functionality into conveniently accessible tabs oriented towards the workflow of developing and using models. The data manager tab contains a data browser and tools for a variety of data manipulations and conversion of data to and from GIS and SQL data repositories to the OPUS data format, geoprocessing tools in external GIS systems such as ESRI and Postgis, and data synthesis tools. The model manager provides infrasructure to create new models, configure them, specify the variables to use as predictive variables, and estimate model parameters using Ordinary Least Squares or Maximum Likelihood methods, depending on the model. The Scenario Manager provides convenient organization of model scenarios and the capacity to launch simulations and monitor them. The Results Manager manages the voluminous output of simulations and provides means to compute and visualize indicators derived from simulation results, and to display these results in maps, charts and tables. The GUI is data-driven from XML files, and can be readily extended by users who wish to add tools, variables, indicators, and other functionality.

5.1.2 Python as the Base Language

One of the most important parts in the system is the choice of programming language on which to build. This language must allow us to build a system with the above characteristics. After considering several different languages (C/C++, C#, Java, Perl, Python, R, Ruby) we choose Python for the language in which to implement Opus. Python provides a mature object-oriented language with good management of the use of memory, freeing up the memory when an object is no longer needed (automatic garbage collection). Python has a concise and clean syntax that results in programs that generally are 1/5 as long as comparable Java programs. In addition, Python has an extensive set of excellent open-source libraries. Many of these libraries are coded in C/C++ and are thus are very efficient. There are also several mechanisms for 'wrapping' other existing packages and thus making them available to Python code.

Some of the Python libraries used by Opus as building blocks or foundational components are:

- *Numpy*: an open-source Python numerical library containing a wide variety of useful and fast array functions, which are used throughout Opus to provide high performance computation for large data sets. The syntax for Numpy is quite similar to other matrix processing packages used in statistics, such as R, Gauss, Matlab, Scilab, and Octave, and it provides a very simple interface to this functionality from Python. See http://numpy.scipy.org/ for more details and documentation.
- *Scipy*: a scientific library that builds on Numpy, and adds many kinds of statistical and computational tools, such

as non-linear optimization, which are used in estimating the parameters for models estimated with Maximum Likelihood methods. See http://scipy.org/ for details.

- *Matplotlib*: a 2-dimensional plotting package that also uses Numpy. It is used in Opus to provide charting and simple image mapping capabilities. See http://matplotlib.sourceforge.net/ for details.
- *SQLAlchemy*: provides a general interface from Python to a wide variety of Database Management Systems (DBMS), such as MySQL, Postgres, MS SQL Server, SQLite, and others. It allows Opus to move data between a database environment and Opus, which stores data internally in the Numpy format. See http://www.sqlalchemy.org/ for details.
- *PyQt4*: a Python interface to the Qt4 library for Graphical User Interface (GUI) development. This has been used to create the new Opus/UrbanSim GUI. See http://www.riverbankcomputing.co.uk/pyqt/ for details.

Python is an interpretive language, which makes it easy to do small experiments from Python's interactive command line. For instance, we often write a simple test of a numarray function to confirm that our understanding of the documentation is correct. It is much easier to try things out in Python, than in Java or C++, for instance. At the same time, Python has excellent support for scripting and running batch jobs, since it is easy to do a lot with a few lines of Python, and Python 'plays well' with many other languages.

Python's ability to work well for quick experiments, access high-performance libraries, and script other applications means that modelers need only learn one language for these tasks. Opus extends the abstractions available in Python with domain-specific abstractions useful for urban modelers, as described below.

5.1.3 Integrated Model Estimation and Application

Model application software in the land use and transportation domain has generally been written to apply a model, provided a set of inputs that include the initial data and the model coefficients. The process of generating model coefficients is generally handled by a separate process, generally using commercial econometric software. Unfortunately, there are many problems that this process does not assist users in addressing, or which the process may actually exacerbate. There are several potential sources of inconsistency that can cause significant problems in operational use, and in the experience of the authors this is one of the most common sources of problems in modelling applications.

First, if estimation and application software applications are separate, model specifications must be made redundantly - once in the estimation software and once in the application software. This raises the risk of application errors, some of which may not be perceived immediately by the user. Second, separate application and estimation software requires that an elaborate process be created to undertake the steps of creating an estimation data set that can be used by the estimation software, again giving rise to potential for errors. Third, there are many circumstances in which model estimation is done in an iterative fashion, due to experimentation with the model specification, updates to data, or other reasons. As a result of these concerns, a design objective for Opus is the close integration of model estimation and application, and the use of a single repository for model specifications. This is addressed in the Opus design by designating a single repository for model specification, by incorporating parameter estimation as an explicit step in implementing a model, and by providing well-integrated packages to estimate model parameters.

5.1.4 Database Management, GIS and Visualization

The extensive use of spatial data as the common element within and between models, and the need for spatial computations and visualization, make clear that the Opus platform requires access to these functions. Some of these are handled internally by efficient array processing and image processing capabilities of the Python Numeric library. But database management and GIS functionality will be accessed by coupling with existing Open Source database servers such as MySQL (www.mysql.org) and Postgres (www.postgresql.org), and GIS libraries such as QuantumGIS (www.qgis.org). Interfaces to some commercial DBMS are available through the SQLAlchemy library. An interface to the ESRI ArcGIS system has been implemented and is being refined.

5.1.5 Documentation, Examples and Tests

Documentation, examples and tests are three important ways to help users understand what a package can do, and how to use the package. Documentation for Opus and UrbanSim is created in both Adobe portable document format (pdf) and web-based format (html, xml), and is available locally with an installation, or can be accessed at any time from the UrbanSim web site. The pdf format makes it easy to print the document, and can produce more readable documents. Web-based documentation can be easier to navigate, and are particularly useful for automatically extracted code documentation.

5.1.6 Open Source License

The choice of a license is an crucial one for any software project, as it dictates the legal framework for the management of intellectual property embedded in the code. Opus has been released under the GNU General Public License (GPL). GPL is a standard license used for Open Source software. It allows users to obtain the source code as well as executables, to make modifications as desired, and to redistribute the original or modified code, provided that the distributed code also carries the same license as the original. It is a license that is intended to protect software from being converted to a proprietary license that would make the source code unavailable to users and developers.

5.1.7 Test, Build and Release Processes

Any software project involving more than one developer requires some infrastructure to coordinate development activities, and infrastructure is needed to test software in order to reduce the likelihood of software bugs, and a release process is needed to manage the packaging of the system for access by users. For each module written in Opus, unit tests are written that validate the functioning of the module. A testing program has also been implemented that runs all the tests in all the modules within Opus as a single batch process. For the initial release process, a testing program is being used to involve a small number of developers and users in testing the code and documentation.

The release process involves three types of releases of the software: major, minor, and maintenance. The version numbers reflect the release status as follows: a release numbered 4.2.8 would reflect major release 4, minor release 2 and maintenance release 8. Maintenance releases are for fixing bugs only. Minor releases are for modest additions of features, and major releases are obviously for more major changes in the system.

The Opus project currently uses the *Subversion* version control system for maintaining a shared repository for the code as it is developed by multiple developers. Write access to the repository is maintained by a core group of developers who control the quality of the code in the system, and this group can evolve over time as others begin actively participating in the further development of the system. A repository will also be set up for users who wish to contribute packages for use in Opus, with write access.

5.2 Introduction to the Graphical User Interface

This section of the documentation provides a tutorial approach to using the Graphical Interface (GUI) that has been added to the OPUS system. This represents a substantial initiative to make UrbanSim and OPUS more user-friendly and accessible to modelers and model users — by reducing the need for programming expertise to use the system effectively to build, estimate, and use model systems for a range of applications. We think the GUI offers a substantial advance in usability, and look forward to user feedback, and contributions from collaborators, to continue building on this foundation.

Before starting the tutorial, please install Opus and UrbanSim on your machine if you haven't already.

The GUI is cross-platform compatible, and has been developed using the open source Qt4 library and the PyQt Python interface to it. Screenshots included in this section will be taken from all three platforms, to give a sense of the look and feel of the GUI on each platform. After launching the GUI from any of these platforms, the main Opus GUI window should be displayed as in Figure 5.1 or 5.2.

The organization of the GUI is based on an expectation that the work flow for developing and using models can be effectively organized into tasks that follow an ordering of data management, model management, scenario management, and results management. The main window of the GUI reflects this work flow expectation, by implementing four tabs in the left-hand panel of the main window labeled *Data*, *Models*, *Scenarios*, and *Results*, plus a *General* tab. Each of the four tabs provides a container for configuring and running a variety of tasks, organized into the main functional areas involved in developing and using a simulation model.

- The *Data* tab organizes the processes related to moving data between the Opus environment and, doing data processing both within Opus, and also remotely in a database or GIS environment. Opus can use Python to pass data and commands to a database system like Postgres or MS SQL Server, or to a GIS system like ArcGIS or PostGIS. Tasks can be organized in the Data Manager as scripts, and run as a batch, or alternatively, they may be run interactively.
- The *Models* tab organizes the work of developing, configuring, and estimating the parameters of models, and of combining models into a model system.
- The *Scenarios* tab organizes the tasks related to configuring a scenario of input assumptions, and to interact with a run management system to actually run simulations on scenarios. Tools to monitor and interact with a running simulation are provided here.
- The *Results* tab provides the tools to explore results once one or more scenarios have been simulated. It integrates an Indicator Framework that makes it possible to generate a variety of indicators, for diagnostic and for evaluation purposes. It also provides functionality to visualize indicators as charts, maps, and tables, and to export results to other formats for use outside of Opus.

To launch the Opus GUI, you will need to run a python script called 'opus.py' in the '/opus/src/opus_gui' directory.[1] If you have used the Windows installer to install Opus, then a Windows `Start` menu item has been added under the Opus menu item under programs, so launching Opus is a simple as selecting the `OpusGUI Opus` menu item. If you did not use the installer, for example, on OS X, or Linux, then open a command window or shell, change directory to the 'opus_gui' directory and type `python opus.py`. In Windows, you can also double-click on the 'opus.py' file in the '/opus/src/opus_gui' directory to launch the GUI.

However it is launched, it will start from a command shell, and this window remains active while Opus is running. Do not attempt to quit this window until after exiting the Opus GUI, or Opus will close also.

5.3 Introduction to XML-based Project Configurations

Notice that at this point there are no contents in any of the tabs. Opus uses XML-based configuration files to flexibly specify the various aspects of a project. In addition, the appearance of the different tabs is also driven from the XML configuration files, so that different parts of the underlying functionality can be dynamically enabled and displayed, or hidden. XML stands for eXtensible Markup Language, and is a generalization of the HTML markup language used to display web pages. It is more flexible, and has become widely used to store content in a structured form.

Let's add add content to the GUI by loading a *Project*, which is in fact, just an XML file containing configuration information. From the main menu, load a project from 'eugene_gridcell_default.xml', which is in the default location of 'opus/project_configs'. The project name and the file name are shown in the title bar of the window. The Opus window should now appear as in Figure 5.3. In this case the project name is "eugene_gridcell" and the file name is 'eugene_gridcell_default.xml'. The project name has an asterisk in front of it (as in Figure 5.3) if the project has unsaved changes. Your project may well be marked as having unsaved changes immediately on opening it, since the GUI automatically scans for simulation runs on startup and enters those in a section of the XML configuration. (The GUI will notify you via a popup window if it adds runs to the configuration.)

One important property of XML project configurations is that they can inherit from other project configurations. In

[1]Note the use of forward slashes in the path. On the Macintosh OS X and Linux operating systems, and in Python, forward slashes are used to indicate separations in the path components. On Windows, backward slashes are used instead. Python can actually use forward slashes and translate them appropriately on Windows or other operating systems as needed, so we will use the convention of forward slashes throughout the text, for generality.

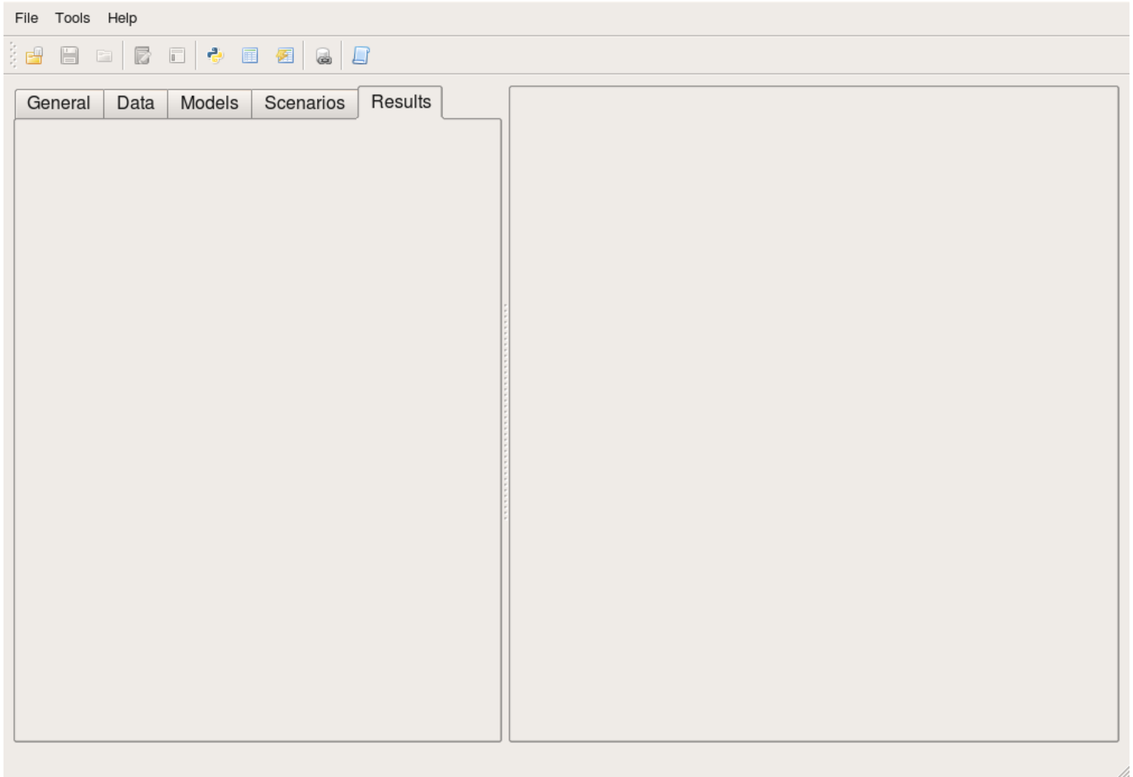


Figure 5.1: Opus GUI Main Window - on Ubuntu Linux

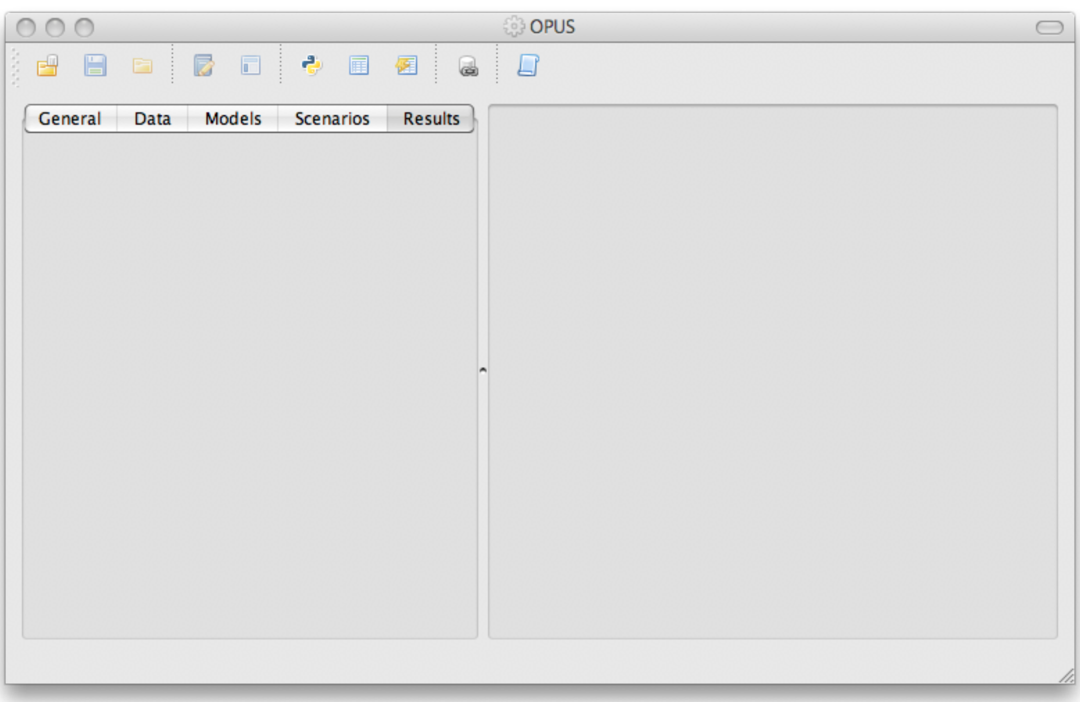


Figure 5.2: Opus GUI Main Window - on Leopard

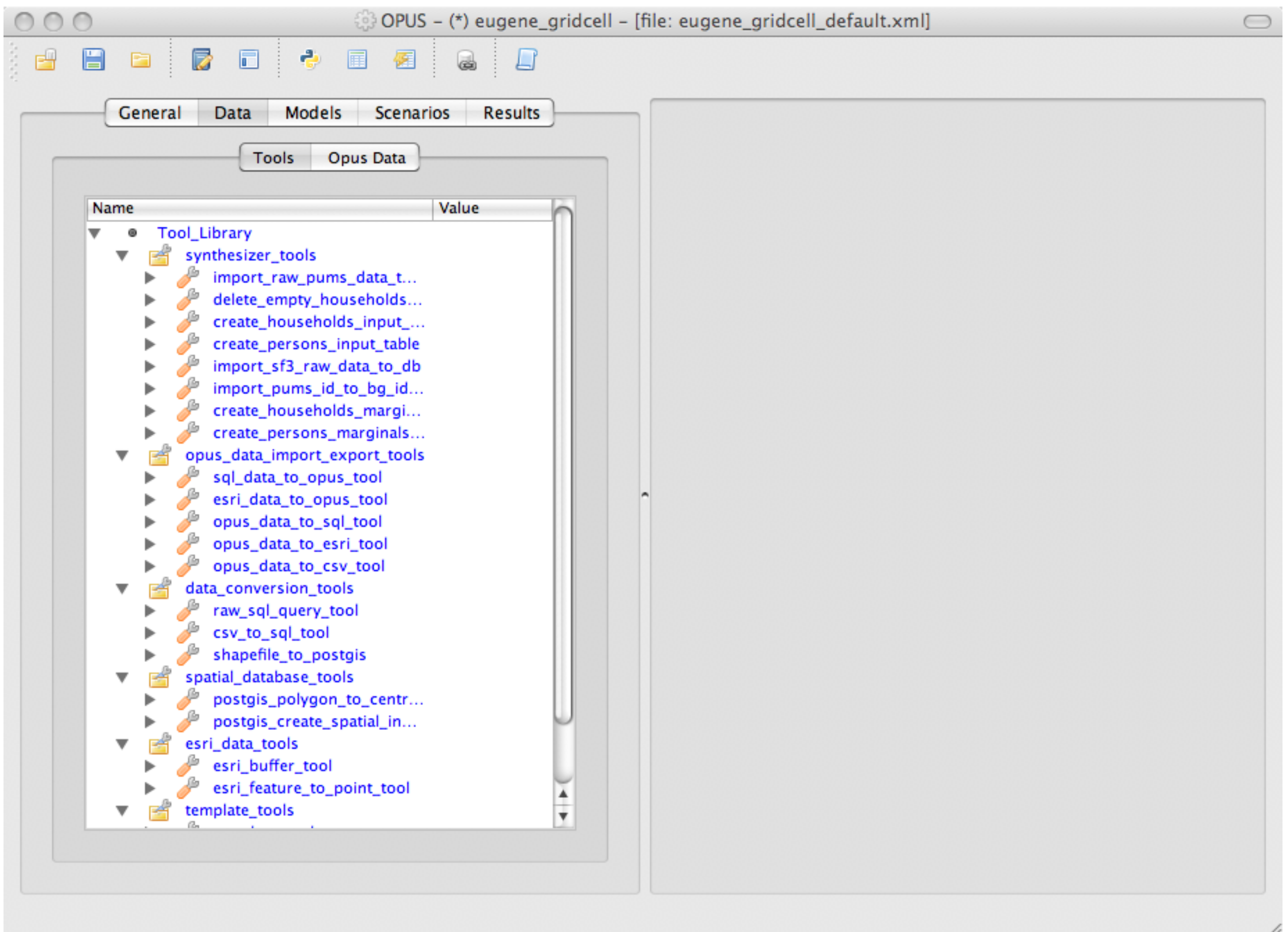


Figure 5.3: Opus GUI main window with the eugene_gridcell project open

practical terms for a user, this means that you can use default projects as templates, or parents, for another project you want to create that is mostly the same as an existing project, but has some changes from it. The new project is called a *child* project. By default, it inherits all the information contained in the *parent* project. However, it can override any information inherited from the parent, and add additional information.

Users should create their own projects in the 'opus/project_configs' directory. This will allow them to keep projects localized in one place, and to avoid editing and possibly corrupting one of the projects that are in an Opus package in the source code tree.

In fact, the 'eugene_gridcell_default.xml' configuration that we just opened initially contains almost no information of its own — virtually everything is inherited from a parent configuration. As you edit and augment this configuration, more information will be stored in the configuration. It can be saved to disk at any time using the "Save" or "Save as ..." commands on the "File" menu. We suggest saving the configuration under a new name, say 'my_eugene_gridcell.xml', and working from that, so that if you want to start over at some point 'eugene_gridcell_default.xml' will still be there in its original state.

5.4 The Variable Library

Variable in Opus and UrbanSim represent quantities of interest. These variables can be used in two principal ways: in specifying models and in computing indicators to assess simulation results. For example, a `distance_to_highway` variable might be used to help predict land values or or household location choices; and a `population_density` variable might be used in computing indicators that are useful for evaluating simulation results. The variable library is a repository for variables defined in the system that are accessible from the GUI. Since it provides a resource that is used throughout the GUI, we access it from the tools menu on the menu bar at the top of the main window, as in Figure 5.4. The screenshot in Figure 5.5 shows a popup window that appears once a user selects the variable library option on the tools menu. Note that the contents of it depend on what project is loaded. In this case, we have the eugene_parcel project loaded, and see the variables that are initially available in this project.

Variables are described in detail later in this manual. Briefly for now, there are three ways to define a variable:

- A variable can be defined using an expression written in a domain-specific programming language. There is a short description of the language later in this chapter. In this chapter we'll only be looking at defining new variables in this way.
- A variable can also be a primary attribute of a dataset (think of these as columns in the input database).
- Finally, a variable can be defined as a Python class. This is an advanced option for complicated variables beyond the scope of the domain-specific programming language — we'll use variables defined this way that are already in the library, but for now won't write any new ones.

Note the buttons at the bottom of this window to add new variables or validate all variables. Adding a new variable defined as an expression is straightforward. There are examples of existing variables defined using expressions in the variable library window — look for variables with the entry "expression" in the "Source" column. The corresponding variable definition is in the right-most column. Note that this definition is executable code — it's not just a description. Expressions are built up as functions and operations applied to existing variables in the library. For example, the expression for wetland is defined as `gridcell.percent_wetland>50`. This defines the creation of a true/false, or boolean, variable that is interpreted as 1 if the gridcell has more than 50 percent coverage by wetland, 0 otherwise. Variables are array-valued, so we are actually computing an array of true/false values for every gridcell with the single expression.

If you click on the add new variable button at the bottom of the variable library window, it opens a dialog box as shown in Figure 5.6. The top entry is the name you want to use for the variable. Let's say we want to create a new variable that is a log of population density. We already have a population density variable defined by gridcell, so we can just take the log of this value. Let's name the variable `ln_population_density`, leave the middle selection as "expression," and fill in a simple expression in the definition area: `ln(gridcell.population_density)`.

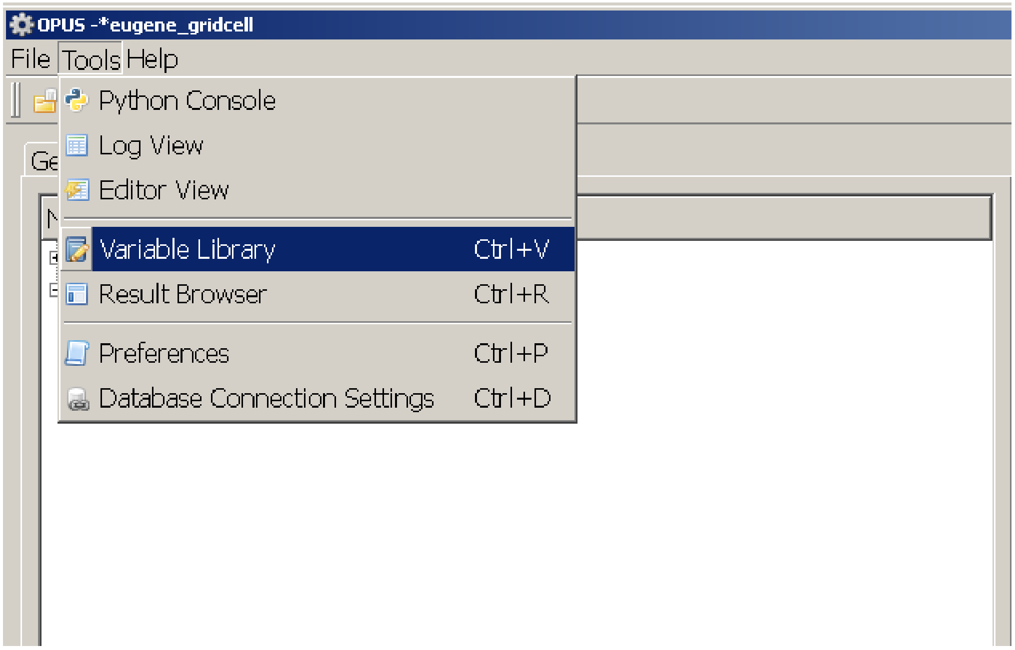


Figure 5.4: Opening the Variable Library from the “Tools” Menu

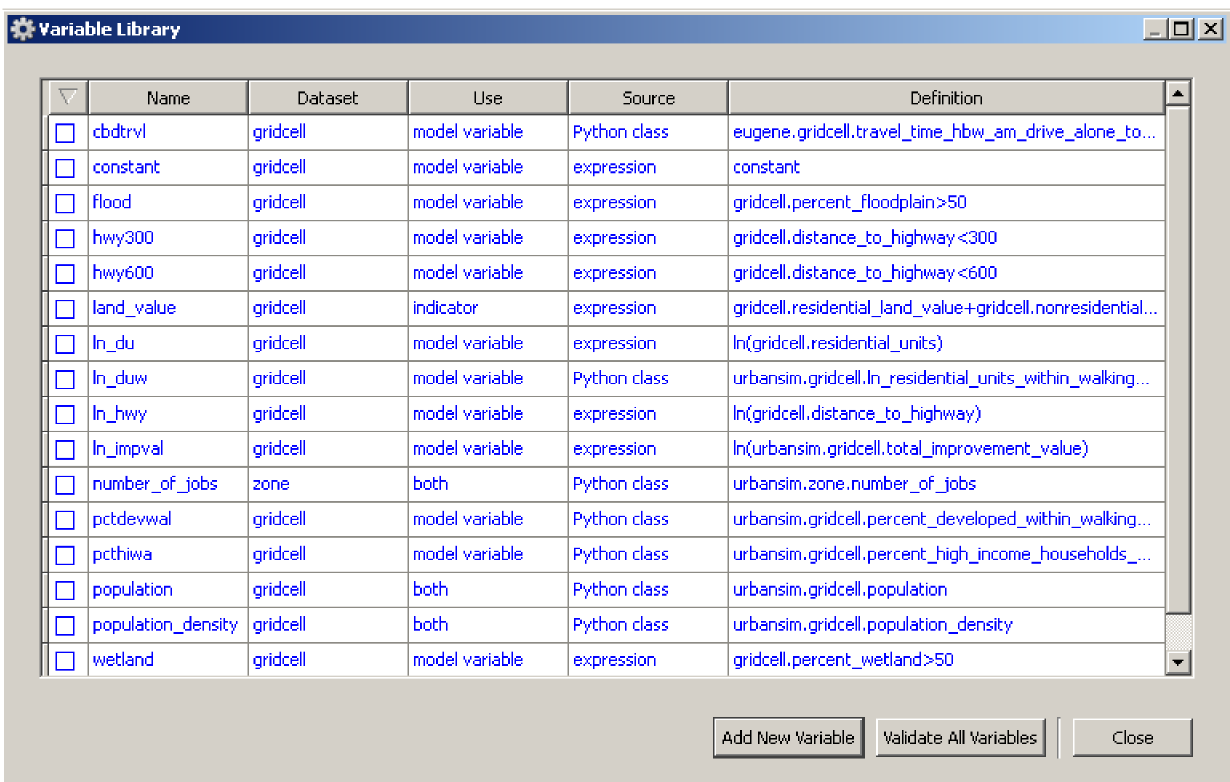


Figure 5.5: Variable Library Popup Window

We're only going to use this variable in defining new models, not as an indicator, so we just check the "Will this variable be used in a model?" box, and leave "Will this variable be used as an indicator?" unchecked. Which boxes you check show up in the "Use" column of the variable library popup window, and also determine whether the new variable appears in lists of variables that you can add to a model specification or use to produce an indicator map; but don't matter for the underlying definition.

The dialog box provides two buttons at the bottom to help you check your new variable. The check syntax button tests whether the expression you have entered passes the Python and expression syntax checkers – in other words, is it syntactically correct. The second allows you to test whether if you apply this expression to your available data, it can successfully compute a result. This is very helpful in determining whether you might have referred to a data element that is not present, or is otherwise not computable with your data. In short, these two tools allow testing whether the variables are in a state that can be computed on the available data.

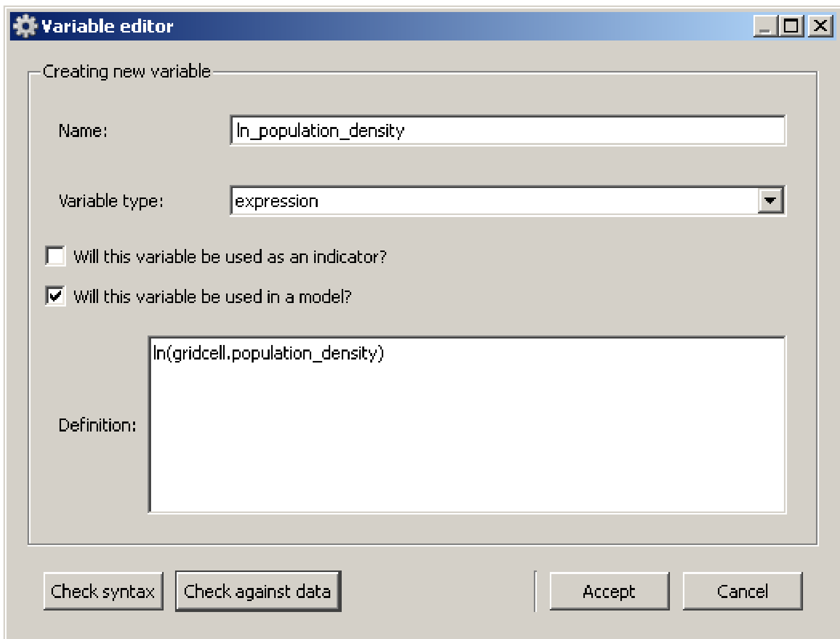


Figure 5.6: Adding a New Variable

We just saw an example of using an expression to define the `ln_population_density` variable. More generally, an expression for a new variable will be written in terms of existing variables, where these existing variables are referenced as a "qualified name" consisting of the dataset name and the variable name, for example, `gridcell.population_density`. Or our new variable can be used in yet another definition by writing *its* qualified name: `gridcell.ln_population_density`.

In building up an expression, we can apply various functions to other variables or subexpressions. For subexpressions that are arrays of floating point numbers, the available functions include `ln`, `exp`, and `sqrt`. We can also use the operators +, −, `*`, /, and `**` (where `**` is exponentiation). The standard operator precedence rules apply: `**` has the highest precedence, then `*` and /, then + and −.

You can use constants in expressions as well, which are coerced into arrays of the appropriate size, all filled with the constant value. For example, `ln(2*gridcell.population_density)` is an array, consisting of the logs of 2 times the population density of each grid cell.

Two subexpressions that are arrays of integers or floats can be compared using one of the relational operators <, <=, ==, >=, >, or != (not equal). We saw an an example of using a relational operation in the `gridcell.percent_wetland>50` expression. `gridcell.percent_wetland` denotes an array of integers, one for each gridcell. The constant 50 gets coerced to an array of the same length, and then the > operator compares the corresponding elements, and returns an array of booleans.

5.5 The Menu Bar

The main menu bar at the top of the OPUS GUI main window has three dropdown menus: File, Tools, and Help. The File menu includes the standard operations of opening a project, saving a project, saving a project under a new name, closing an OPUS Project, and finally exiting the OPUS GUI. Help offers an About option which produces a dialog box with information about OPUS and a set of links to the UrbanSim website, online documentation, and the GNU License. The Tools menu provides access to several general tools, described below.

Most of the items in the main menu bar are accessible from a secondary menu bar just above the tabs on the left side of the OPUS GUI window. Hovering over each icon will yield a tooltip with the item's description.

5.5.1 Tools

The Tools menu, shown in figure 5.7, enables users to adjust settings and preferences, as well as opening different tabs in the right set of tabs. The items labeled "Log View" and "Result Browser" will each open new tabs on the right. The Result Browser is covered in greater detail in section 5.10.2. The items labeled "Variable Library," "Preferences," and "Database Connection Settings" each open a popup when clicked. (On the Macintosh, the "Preferences" item is under "Python" rather than "Tools.") The Variable Library is further discussed in Section 5.4.

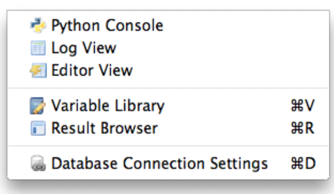


Figure 5.7: Tools Menu

5.5.2 Preferences

The Preferences dialog box changes some user interface related options in the OPUS UI. The dialog box is split into two sections, font preferences and previous project preferences. The font preferences section allows users to adjust font sizes specific to different areas of the GUI. The previous project preferences section contains a checkbox allowing users to open the most recently opened project each time OPUS GUI is started, this is turned off by default. Changes to the user preferences take effect as soon as either the "Apply" or "OK" buttons are clicked.

5.5.3 Database Server Connections

Database connections can be configured in the Database Server Connections dialog launched from the Tools menu. The Database Server Connections dialog, pictured in Figure 5.8, holds connection information for four database servers. Each connection is used for a specific purpose. While there are four different connections that must be configured, each may be configured to use the same host. Every connection requires a protocol, host name, user name, and password to be entered. Editing the protocol field produces a drop down of database protocols that UrbanSim is able to use. If a server has been setup for UrbanSim's use choose the protocol that corresponds to the type of SQL server being used. If no SQL server is setup for a particular use, SQLite may be used. SQLite will create a local flat-file database instead of a remote server. UrbanSim currently supports MySQL, Microsoft SQL Server, Postgres, and SQLite.

The Database Connection Settings are saved when the Accept Changes button is pressed, ensuring that all future database connections will be made using the new settings. Database connections that are still in use while the database connection settings are being edited will not be changed until the connection is reestablished, for this reason it may be necessary to reopen any open project after changing the database connection settings.

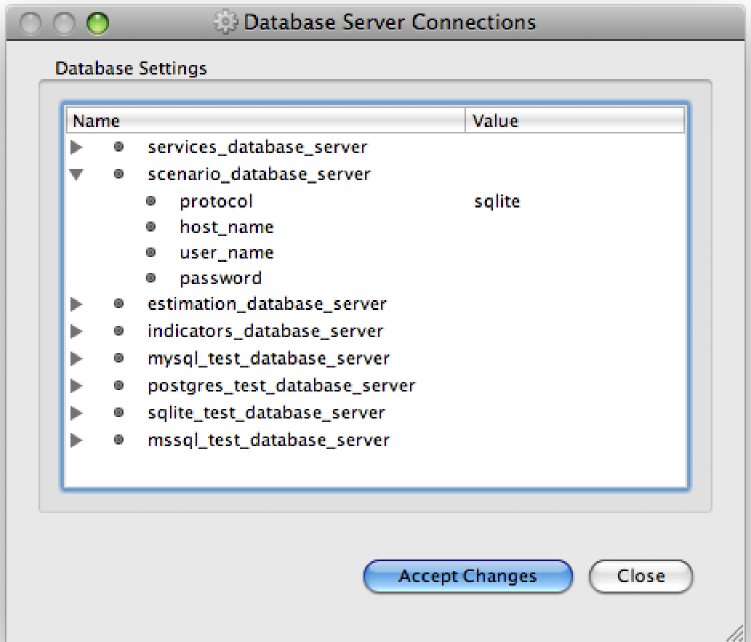


Figure 5.8: Database Connections

5.6 The General Tab

The General tab is responsible for displaying general information about the current project. Figure 5.9 shows the General tab displaying information for the "eugene_gridcell" project. This information includes a brief description of the project, the project name, the parent project configuration, and a list of available datasets that can be used in computing the values of expressions. The "parent" field identifies the XML project from which the currently open project inherits. Add a dataset to the "available_datasets" field if you have any extra datasets to be added to the project. The "dataset_pool_configuration" field includes a field named "package_order" that gives the search order when searching for variables implemented as Python classes; it is unlikely that you'll want to change it.

The fields of the General tab can be edited by simply double clicking the value side of a field that is part of a project. If a field is displayed in blue, this field is being inherited from the parent project, and must first be added to the current project before editing can be done. To add a field to the current project, right-click and select "Add to current project". Once added, the field may be edited as usual.

If you edit the "parent" field(not a typical operation), immediately save and close the project, and then re-open it, so that the inherited fields from the new parent will be shown

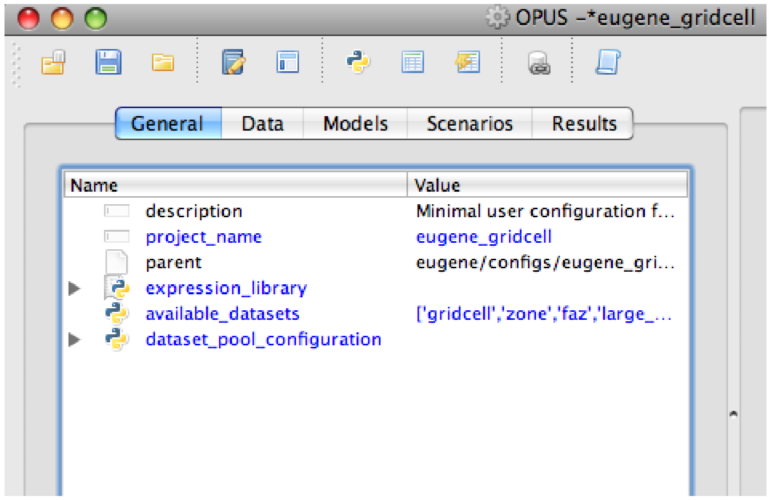


Figure 5.9: The General Tab

5.7 The Data Manager

The Data Manager has two primary purposes, each reflected in the sub-tabs. One tab, the Opus Data tab, is for browsing, viewing, and exporting data from the Opus data cache. The other tab, the Tools tab, is a place for storing and executing various tools provided by the Opus community or tools you have written.

5.7.1 Opus Data Tab

The Opus Data tab is a file browser that defaults to the folder in which your project creates data. This folder name is composed from the default location for the Opus files, followed by 'data', followed by the project name. The project name for the 'eugene_gridcell_default.xml' project is "eugene_gridcell." (This is given in the "project_name" element in the xml.) Thus, if you installed to 'c:/opus', and you are opening the Eugene sample project at 'c:/opus/project_-configs/eugene_gridcell_default.xml', the data folder for this project is 'c:/opus/data/eugene_gridcell'. That is the folder that this view starts at. Any subfolders and files are displayed in the tree view. See Figure 5.10.

There could be any number of subfolders here, but by default you will find a 'base_year_data' folder, and a 'runs' folder. The base_year_data folder will normally contain an Opus 'database' folder. An Opus database folder is any folder containing Opus 'datasets'. Often Opus database folders are titled with a year, such as 2000. Opus datasets are folders containing Opus 'data arrays.' Opus datasets are equivalent to the tables in a database. Opus data arrays are equivalent to the columns in a table, and are simply numpy arrays that have been written to disk in a binary format. See Figure 5.11.

The Opus data arrays are referred to throughout the documentation as 'primary attributes.' Primary attributes are the actual data columns in a dataset. Computed attributes are attributes computed from primary attributes via expressions. For instance, if a parcels dataset contained the primary attributes population and area, a computed attribute called population_density could be computed by using the expression `population_density = population/area`. Once this expression is entered and stored in your project in the Variable Library, it can be used in a model and would be computed as needed.

Viewing and Browsing an Opus Data table

To view and browse the contents of an Opus dataset, right-click a data table, then select 'View Dataset'. This will bring up a new tab on the right-hand side of the Opus GUI window that will display some summary statistics about

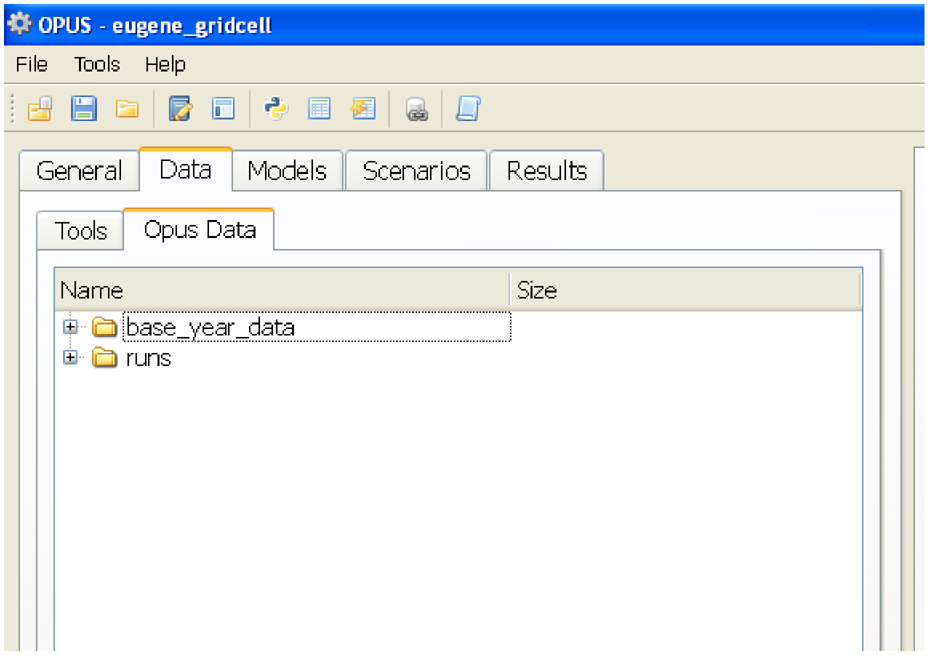


Figure 5.10: The Opus Data Tab

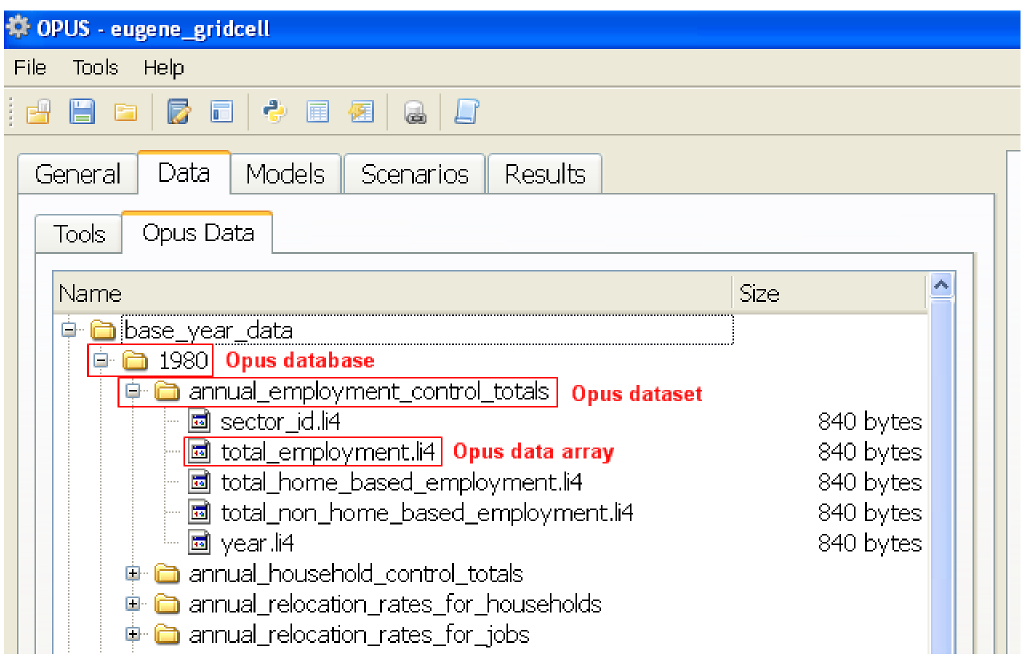


Figure 5.11: Opus databases, datasets, and arrays

the dataset, and a table view of the raw data that can be browsed and sorted by clicking the column name. See Figure 5.12 for an example of browsing a data table.

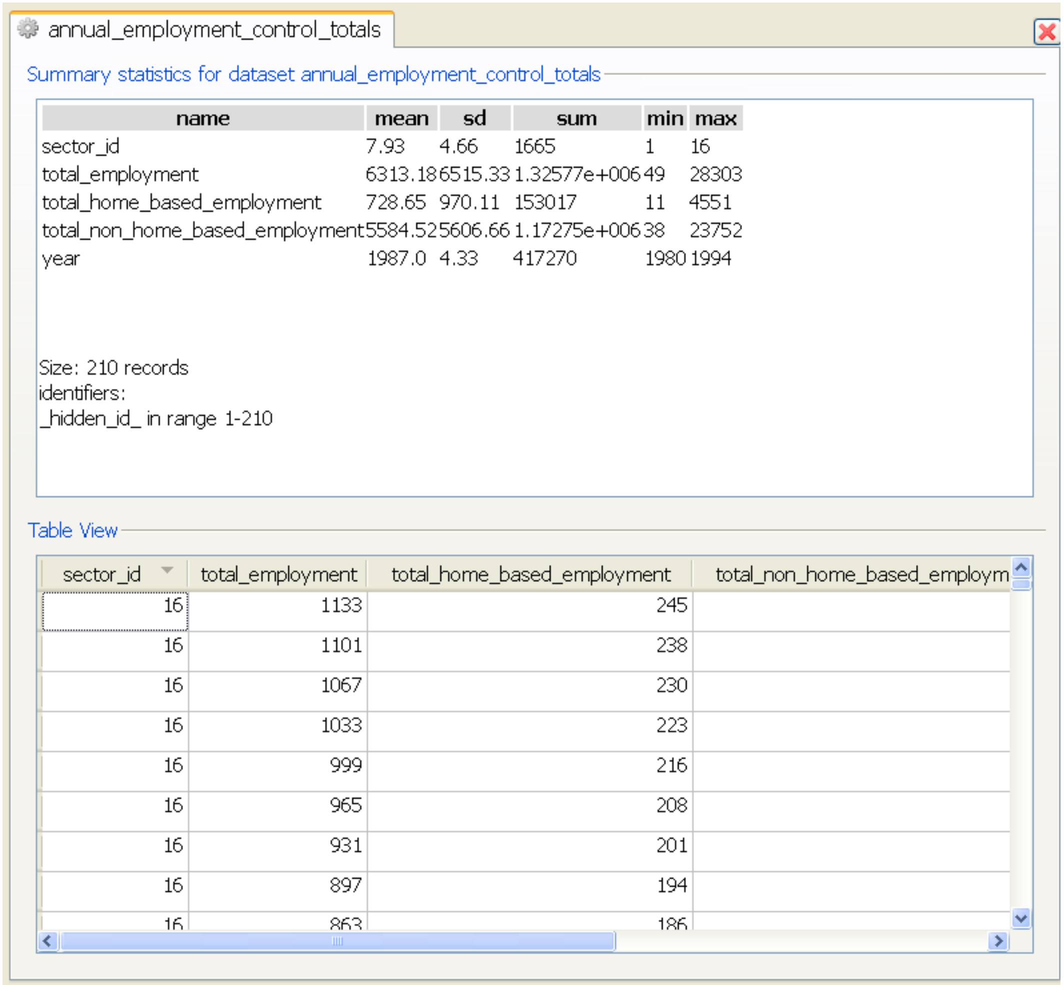


Figure 5.12: Viewing and browsing an Opus dataset

Exporting an Opus Data table

An Opus dataset can be exported to another format for use in other applications. By default there are 3 options: ESRI, SQL, and CSV. To export a dataset, right-click a dataset, choose 'Export Opus dataset to,' then click your choice. See Figure 5.13 for the right-click menu. You will then see a pop-up window with the respective export tool with the parameters partially filled in based on which dataset you clicked. These are the same tools that you will find in the Tools tab of the Data Manager. For more information on the individual tools see the help tab on each tool.

5.7.2 Tools Tab

The Tools tab is an area to collect and execute tools and batches of tools provided with the interface, or it can be extended with tools that you write. A Tool is simply any script that is written in Python and executed by the interface.

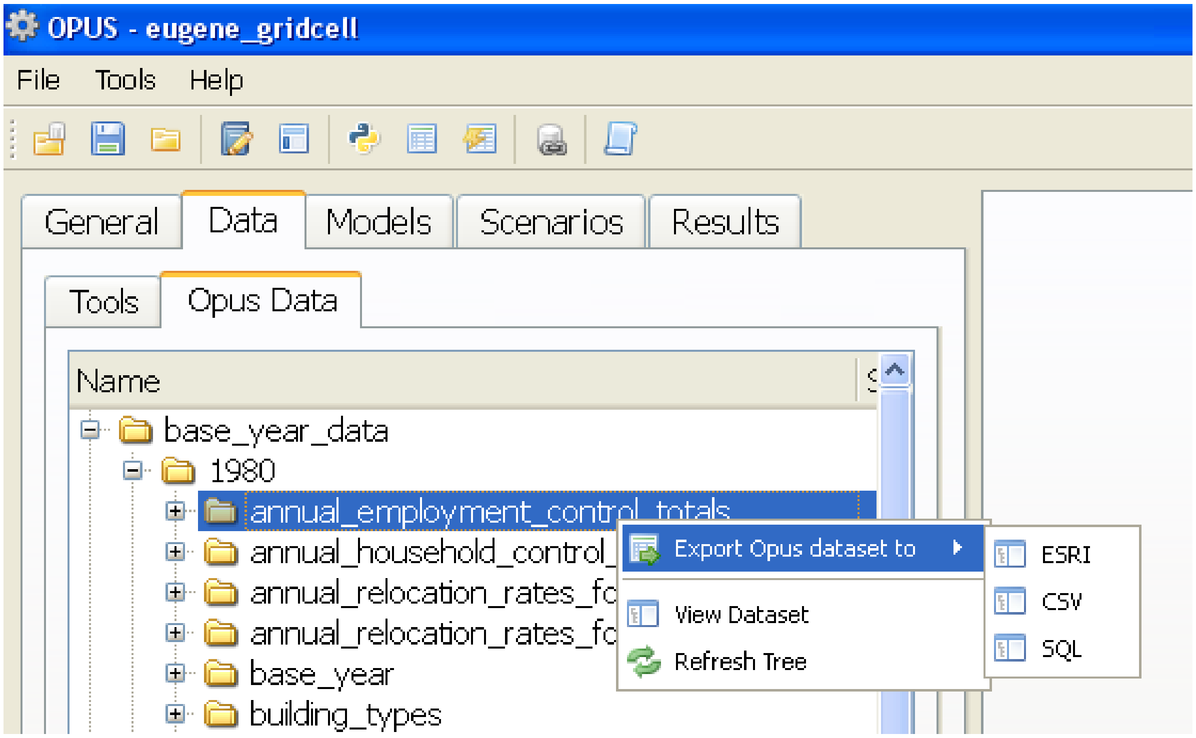


Figure 5.13: Exporting an Opus dataset

Tool Library

The Tool Library is a place to collect and organize your tools. Tools can also be executed directly from the library in a 'one-off' manner, meaning that you can supply parameters to the tool and execute it without storing those parameters for future use. To execute a tool from the library, simply right-click it and choose 'Execute Tool...', see Figure 5.14. This will pop-up a window in which you can supply parameters to the tool then execute it.

New tools can be written and added to the tool library fairly easily. The best way to explain this is to use an example. A 'template_tool' has been provided so you can see how it works. Feel free to execute the template_tool, it just implements a simple loop and prints the results to the tool's log window. The template_tool's code and associated XML display everything that is needed to add a tool to the interface. See the code in the source code tree at /opus_-gui/data_manager/run/tools/template_tool.py. A tool also needs XML configuration data in an Opus project. To view the XML configuration data for the template_tool, open urbansim.xml in an XML editor from the source code tree at /urbansim/configs and search for template_tool.

At the time of this writing new tools must be placed in the source tree at /opus_gui/data_manager/run/tools in order to run correctly. There are plans to create an additional 'user tools' folder where tools could also be placed. Also, at this moment, the XML must be hand written to ensure that the tools show up properly in the interface and execute correctly. There are some right-click functions in the Tool Library to assist with the XML editing (to add a new tool, create parameters for it, etc.) but these functions are in a beta state.

Once a new tool and its associated XML is written properly, the Tool Library will display the tool and dynamically populate the pop-up dialog box with the proper parameters based on the XML configuration. The tools are quite flexible. Although the initial tool must be written using Python, there is no limit placed upon what one can do. For starters, there are tools provided in the interface that make OS calls to external executables (e.g. ogr2ogr.exe), databases, and myriad other libraries to accomplish various tasks (e.g. ESRI geoprocessing). Feel free to browse the source code for any provided tool along with the XML configuration to see some possibilities.

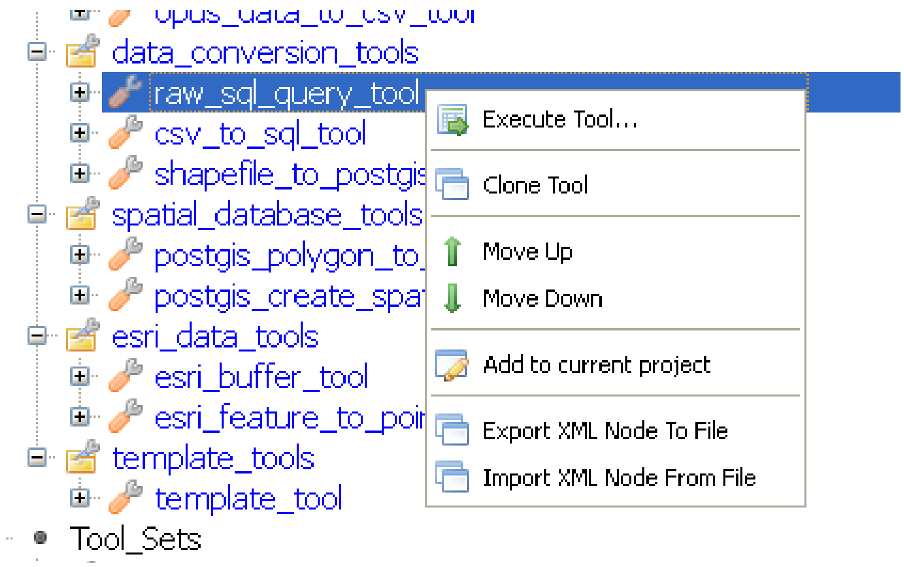


Figure 5.14: Executing a tool

Tool Sets

Tool Sets are simply collections of tools from the Tool Library with parameters stored so they can be executed repeatedly or in order in a batch manner. Tool Sets can contain any number of tools from the Library. A new Tool Set can be created by right-clicking Tool_Sets and choosing 'Add new tool set.' This adds a new Tool Set to the bottom of the list. It can be renamed by double-clicking it and typing in a name, taking care to not use spaces or a leading integer as these are invalid in XML nodes. Once you have a new Tool Set, tools from the Library can be added to it by right-clicking a Tool Set and choosing 'Add Tool to Tool set.' See Figure 5.15 for an example of what this looks like.

From this window, choose a tool from the drop down menu, fill in the parameters, then click 'Add Tool.' The tool is added to the Tool Set and the parameters you entered are stored in the project XML file. This configured tool can now be executed by itself with those parameters, or executed as part of a batch in the Tool Set. Tools in a Tool Set can be re-ordered by right-clicking them and choosing to move them up or down, and all of the tools can be executed in the order they appear by right-clicking a Tool Set and choosing 'Execute Tool Set'.

5.8 The Models Manager

The model manager tab in the GUI provides the functionality to create models of various types, configure them, specify the variables to use in them, and then estimate their parameters if they have a form that needs to be estimated – such as regression models or discrete choice models.

5.8.1 Creating an Allocation Model

To demonstrate the process of creating models in the GUI, let's begin with a simple allocation model, which does not have any parameters to estimate and represents a straightforward model to configure. Say we want to create a model that allocates home-based jobs to zones, and lack sufficient data to specify a choice model or regression model for this purpose. Home-based jobs are those jobs that are located in properties that are residential in character. Assume that we have no behavioral information about this problem, other than the insight that home-based jobs are... home-based. So we can infer that we should probably allocate these jobs to places that have housing (or households). In allocating these jobs to zones (traffic analysis zones used in the travel model), we can count how many residential units are in

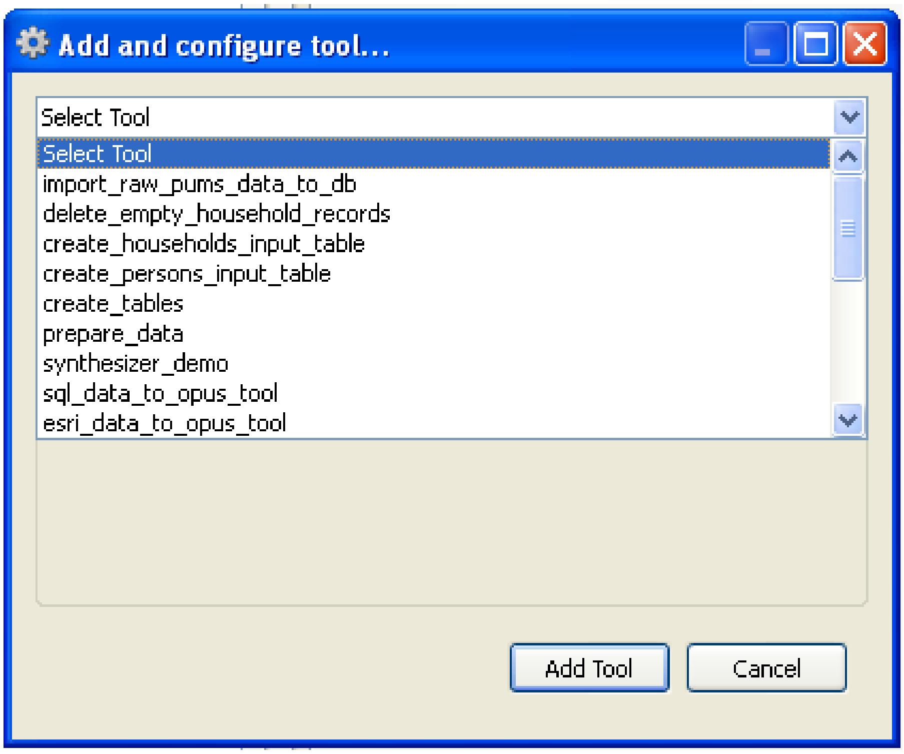


Figure 5.15: Adding a tool to a Tool Set

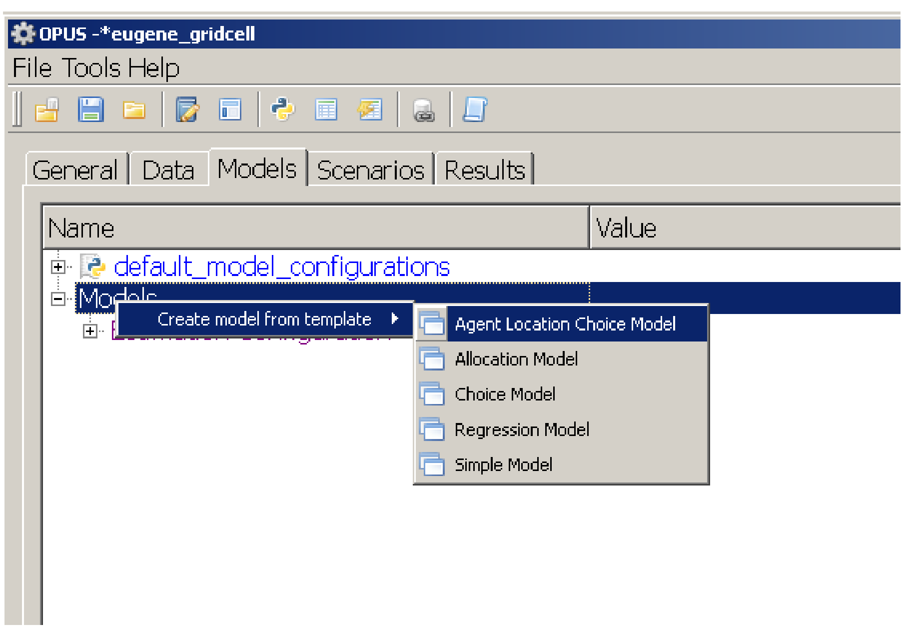


Figure 5.16: Creating a New Model from a Template

each zone, and use this as the weight to allocate the total home-based jobs to zones. That is, we want to proportionately allocate home-based jobs to zones, weighted by the number of residential units in the zone. This is equivalent to saying that we want each residential unit to have an equal probability of receiving a home-based job (assuming that we do not have any information to suggest which residential units would be more likely than others to receive such a job).

The next consideration is the capacity of zones to absorb home-based jobs. One simplifying assumption we could make is that there is a maximum of one home-based job per residential unit in a zone. On average, our aggregate information suggests that most residential units do not have a home-based job, so this assumtion should not be constraining.

We now have all the information we need to specify a model for home-based jobs. We will name the model allocate_-home_based_jobs, to be descriptive. The table below contains the *arguments* we will need to use in creating this model in the GUI.

Table 5.1: Creating an Allocate Home Based Jobs Model

Configuration Entry	Value
Model Name	allocate_home_based_jobs_model
Dataset	zone
Outcome Attribute	home_based_jobs
Weight Attribute	zone.aggregate(building.residential_units)
Control Totals	annual_employment_control_totals
Year Attribute	year
Capacity Attribute	zone.aggregate(building.residential_units)

The create new model dialog box (Figure fig:create-model) contains several kinds of model templates we could create a model from. One of these is Allocation Model. The capacity to create new allocation models, such as this, is now available in the Opus GUI. Select Allocation Model from the list, and a new dialog box appears, with several fields to fill in. Fill in the fields with the contents from Table 5.1, and save it. Once this is done, it will appear in the list of models under the Models section of the Model Manager tab. It is now a fully enabled model, and can be included in a simulation run.

It should go without saying (but doesn't), that creating models through the GUI, with a few mouse clicks and filling in a few fields in a dialog box, is much, much easier than it has been in the past. One does not need to be an expert software developer in order to create and use interesting and fully functional models in OPUS.

5.8.2 Creating a Regression Model

Regression models are also simple to create and specify in the Opus GUI, and can be estimated and simulated within the graphical interface. Assume we want to create a model that predicts population density, using the population per gridcell as the dependent variable and other attributes we can observe about gridcells as independent (predictor) variables. Note that this is not a very useful model in this context since we actually have a household location choice model to assign households to gridcells – so this model is for demonstration purposes only.

To create this model in the Opus GUI, right-click again on Models, and select in this case Regression Model to generate a new dialog box for this model template, as shown in Figure 5.18. We just need to provide three arguments in the dialog box - a name to assign to the new model (we will use population_density_model), a dataset to contain the dependent variable (gridcell), and the name of the dependent variable (population_density) - which should exist in the base year, or be an expression to compute it from other attributes already in the data.

Once the values have been assigned to the configuration of the new model, and you click OK on the dialog box, the model is added to the list of models under Models. If you expand this node by clicking on the plus sign to the left of the new land price model entry, you will see that it contains a specification and a structure node. Expand the specification node, and you will find some additional detail, including a reference to submodels, and a variables entry. We will ignore submodels for now – it is a means of specifying that you would like to specify the model differently for

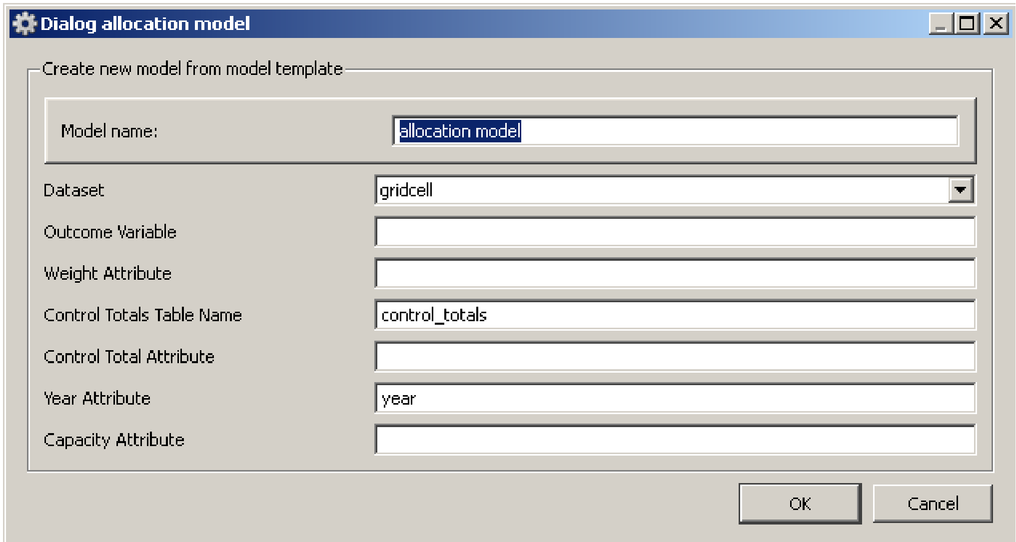


Figure 5.17: Creating a New Allocation Model from a Template

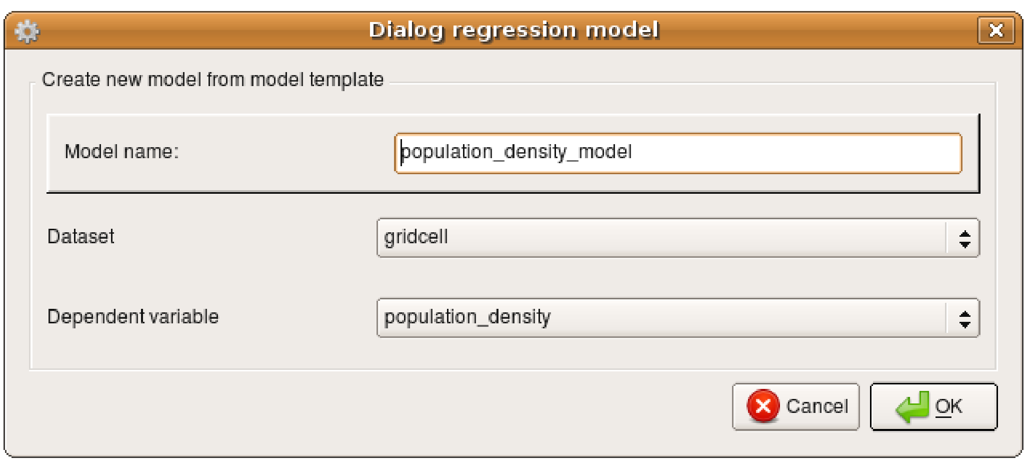


Figure 5.18: Creating a New Regression Model from a Template

different subsets of the data. For now we will just apply a single specification to all the data, to keep this a bit simpler. We can now move to the task of specifying and estimating this model.

Right-click on the variables node, and click on Select Variables, as shown in Figure 5.19. At this point a window should appear as shown in Figure 5.20 that is essentially the same as the variables library window you encountered earlier. There is a column of check-boxes at the left hand side of the window which you can use to identify the variables you want to include as independent variables, or predictive variables, for this model. The button at the bottom allows you to accept the selection, which then updates the list of variables in the model specification. Try adding a constant term, since this is a regression and we need an intercept, or a base value. Also add a variable like population density. Now accept the selections.

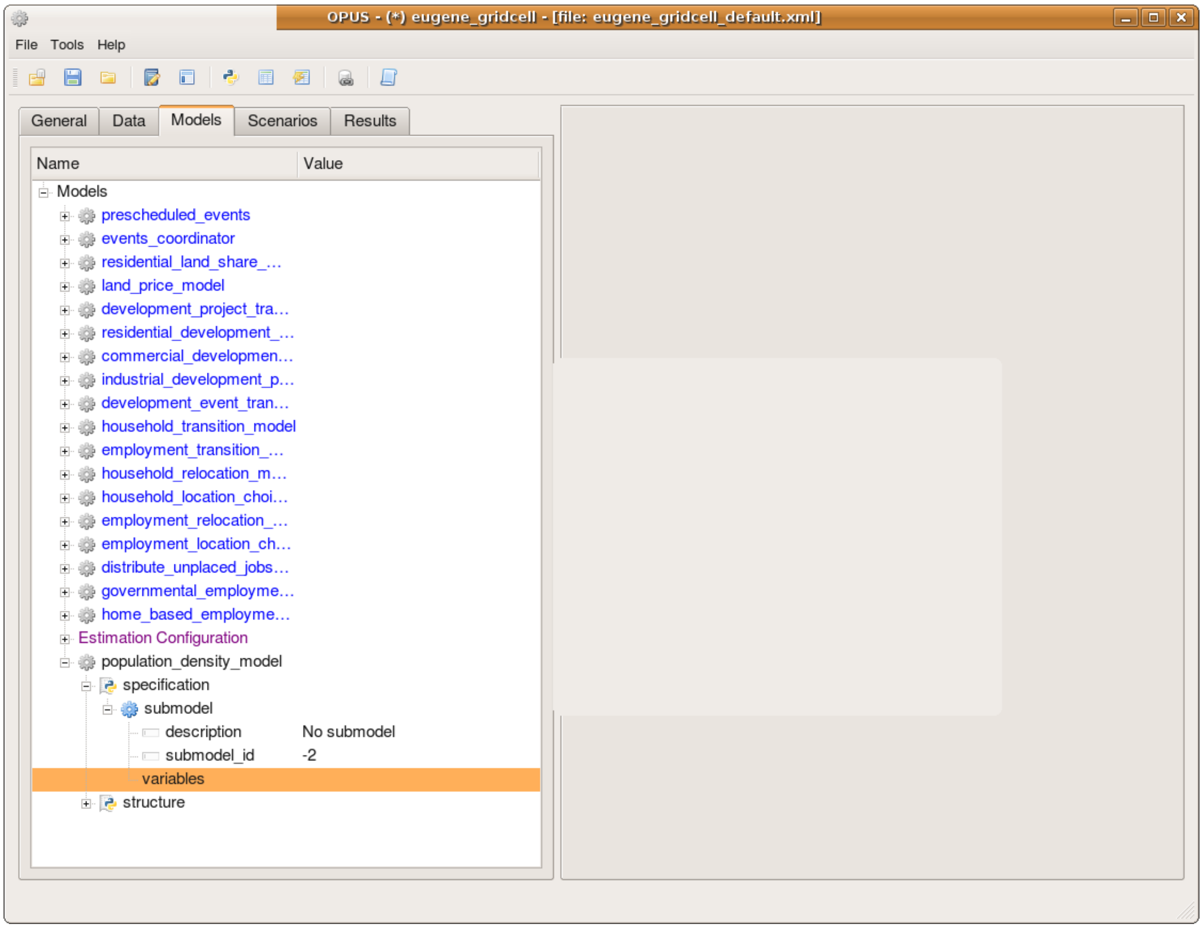


Figure 5.19: Specify the New Population Density Model

Once the model specification has been entered, we can estimate the model parameters using Ordinary Least Squares by right-clicking on the population density model and selecting Run Estimation, as shown in Figure 5.21. Once this has been clicked, a new tab appears on the right hand side of the main window, to interact with the model estimation. Click on the start estimation button, and within a few seconds you should see the estimation results appear in this tab, as shown in Figure 5.22.

We can see from the results that the constant and travel time to the CBD, and also land value were quite statistically significant, and that they explain around 28 percent of the variation in population density in Eugene. Clearly this is a toy model, but adding other variables in this way can increase the explanatory power to a quite useful level, and as you can see modifying the specification and estimating the model is not difficult to do.

One other note at this point is that the specification and estimation results are automatically stored, if you request this,

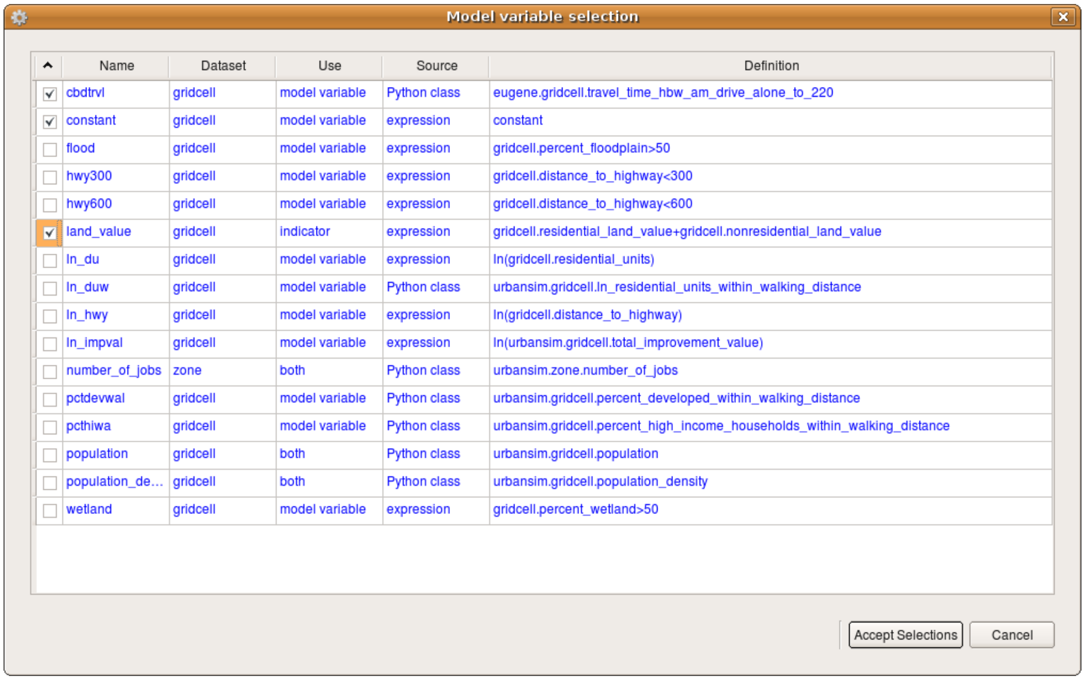


Figure 5.20: Select Variables for Specification

as shown in Figure 5.23. Once the estimation is done, then, the model is ready to use in a simulation, or predictive mode. More on this in the Scenario Manager section.

5.9 The Scenarios Manager

5.9.1 Running a Simulation

Once a project has been developed, including the data to be used in it, and the model system has been configured and the parameters for the models estimated, the next step is to create and run a scenario. In the eugene_gridcell project, a baseline scenario has already been created and is ready to run. To run this scenario, in the Scenario Manager, right-click with the mouse on the Eugene_baseline entry and select "Run this Scenario." At this point, a frame should appear in the right hand side of the Opus window, as shown in Figure 5.24.

The frame on the right contains an option to start the simulation run and another to cancel it. Start the run with the `Start Simulation Run ...` button. Note that the button's name changes to `Pause Simulation Run ...`. The window will now update as the simulation proceeds, with progress bars and labels being updated to show the changing state of the system, such as which year the model is simulating and which model is running. If the simulation completes successfully, the "Total progress:" bar will say "Simulation ran successfully" after it, and the "Year progress" bar will say "Finished" (Figure 5.25).

This simulation run then is entered into the simulation runs database, which can be subsequently inspected via the "Simulation_runs" node in the Results Manager (Section 5.10.1). Indicator results from the simulation can also be generated using other tools in the Results Manager (Section 5.10.2).

That's it for the basics of running a simulation! However, there are various options for selecting, configuring and running a scenario, which are described in the following subsections.

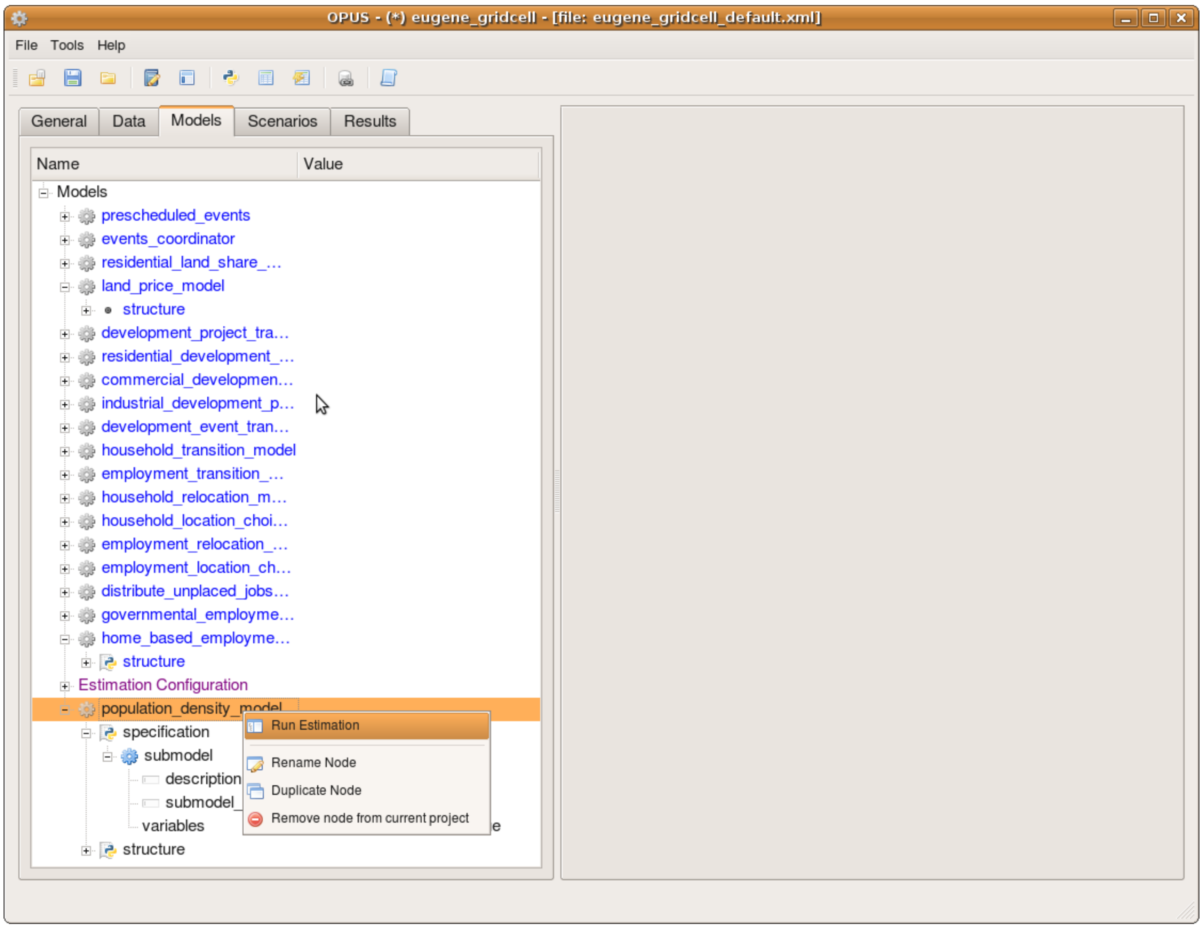


Figure 5.21: Estimate the New Population Density Model

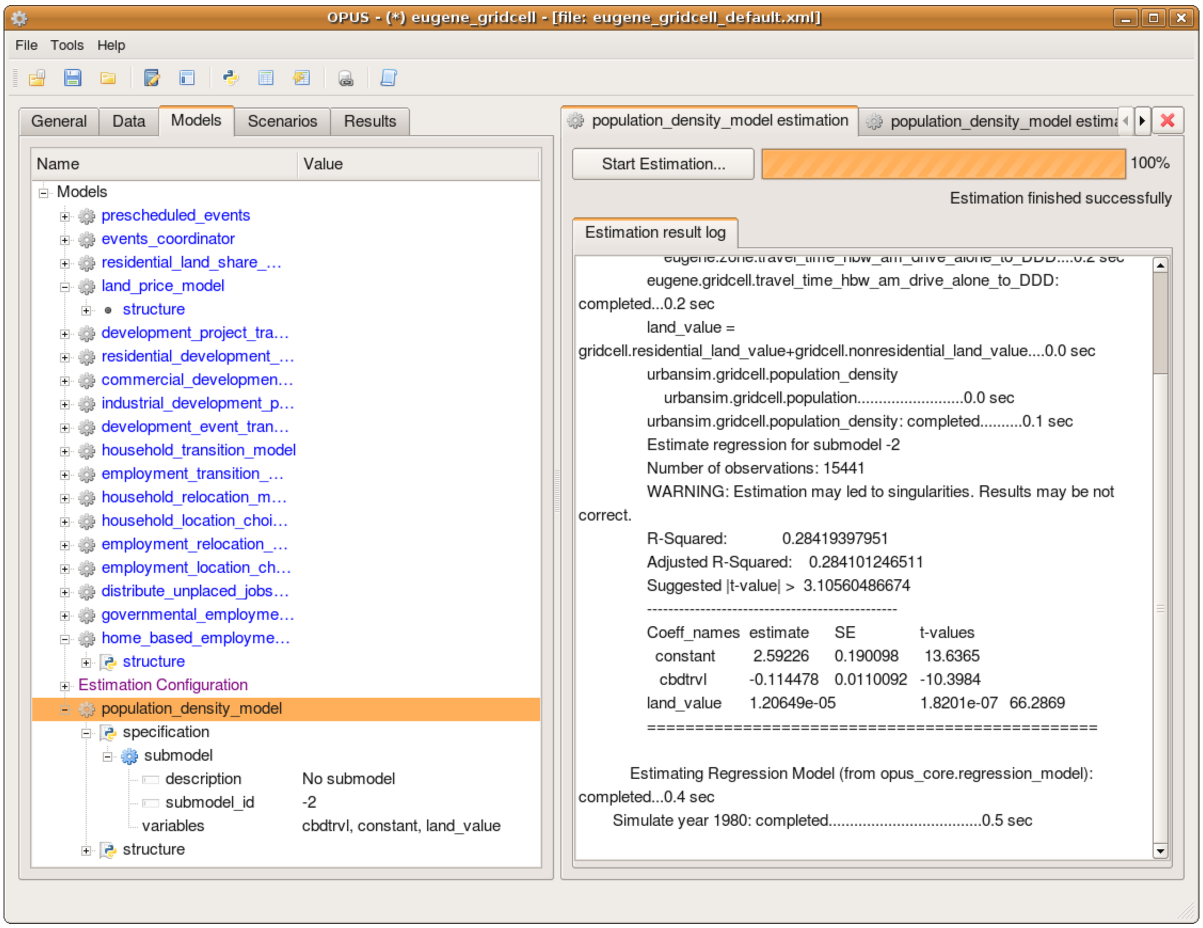


Figure 5.22: Estimation Results

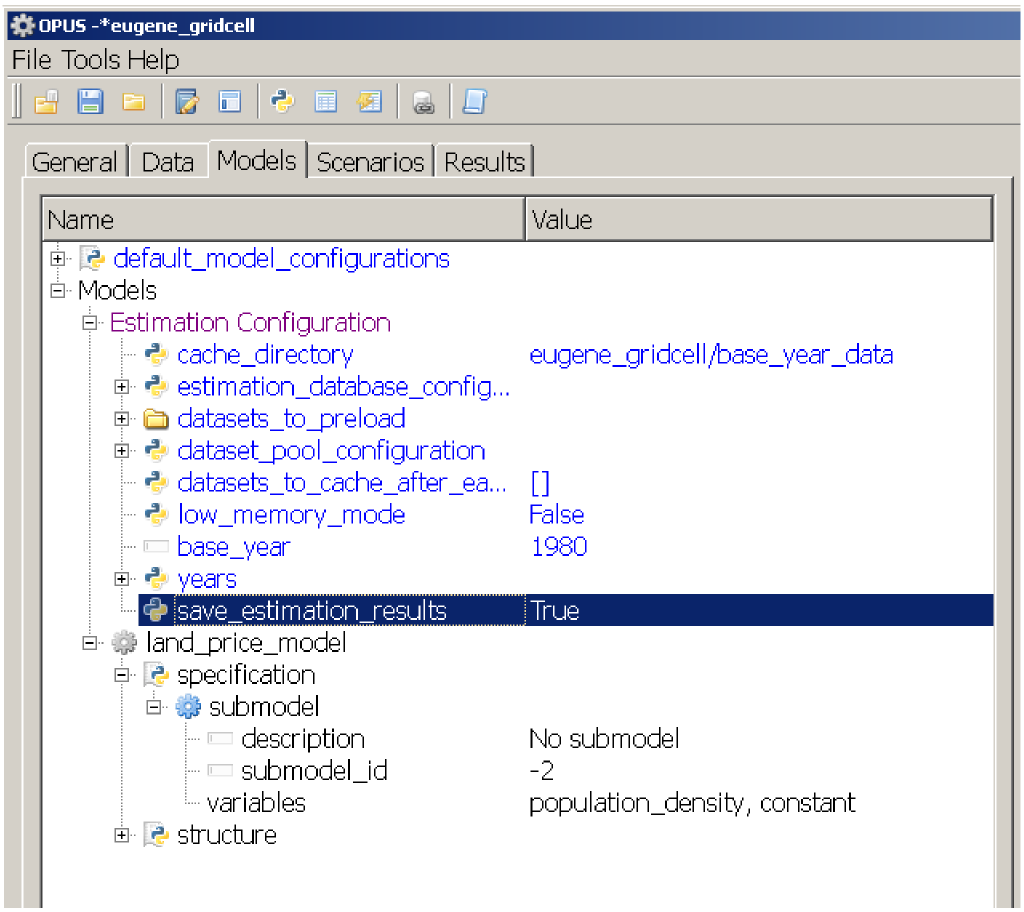


Figure 5.23: Save Estimation Results Flag

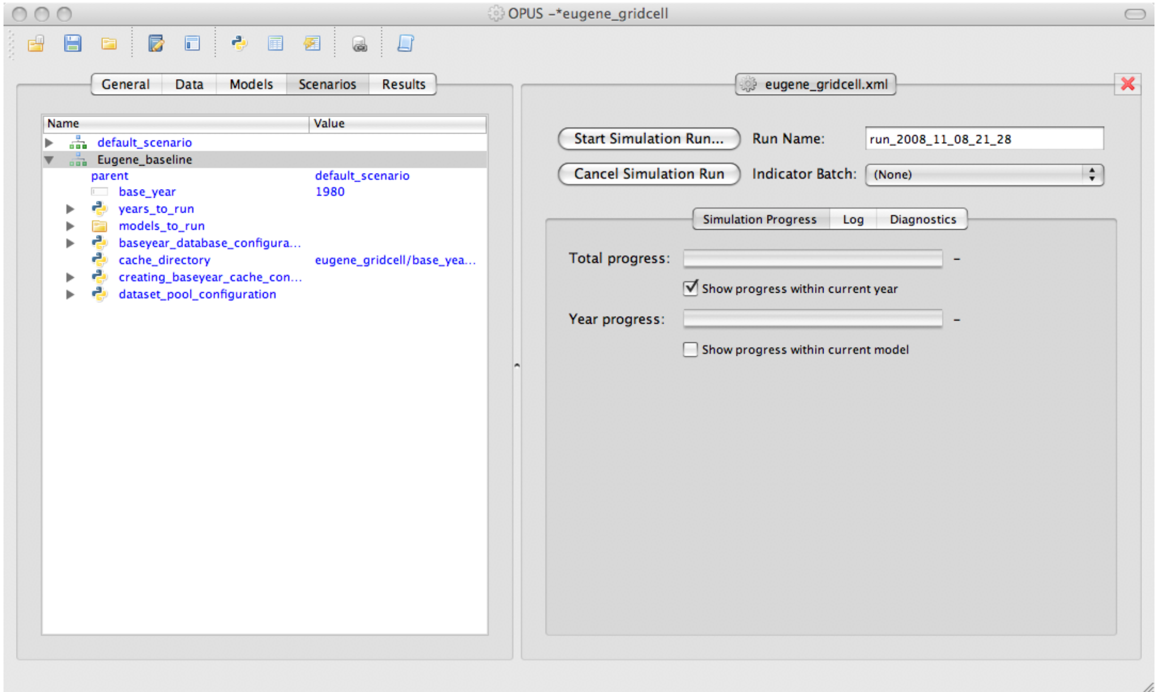


Figure 5.24: Starting a simulation on the Eugene baseline scenario

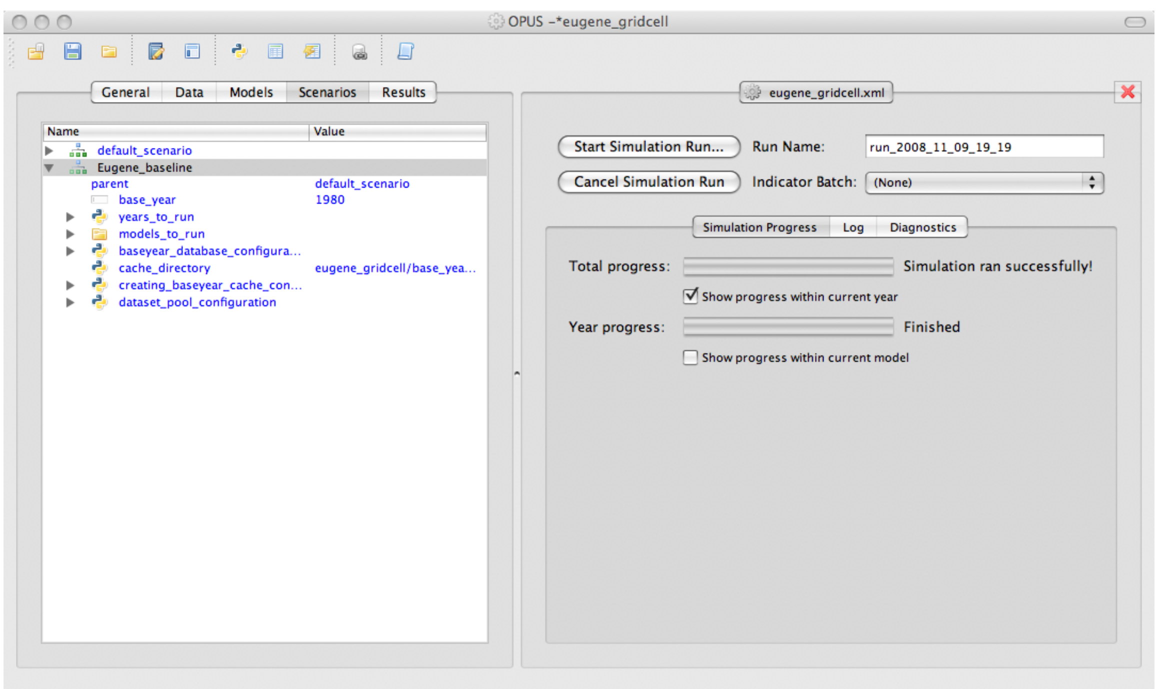


Figure 5.25: A completed simulation run

Options for Controlling the Simulation Run

Here are the aspects of controlling the simulation run via controls in the frame on the right. The results of this simulation are entered into the simulation runs database under the “Run Name” (upper right hand part of the pane). This is filled in with a default value consisting of “run_” followed by the date and time; edit the field if you’d like to give the run a custom name. Immediately under that field is a combo box “Indicator Batch:”. If you have defined and named a batch of indicators that can be run, you can select one of these from the list, and the indicators will automatically be run at the conclusion of the simulation. See Section 5.10.2 for information on indicator batches.

As mentioned above, once you start the simulation the `Start Simulation Run ...` button label changes to `Pause Simulation Run`. If the pause button is pressed while the model system is running, a request to pause the model is triggered, and once the current model in the model system is finished, the system pauses until you take further action by pressing either the `Resume Simulation Run...` or the `Cancel Simulation Run` button. The `Cancel Simulation Run` button is also available while the simulation is running. (As with “Pause,” “Cancel” generally won’t happen immediately, but only after the current model in the model system is finished.)

Options for Monitoring the Simulation

Moving down the frame, there is a button for selecting views in the bottom of the screen. The default is “Simulation Progress,” which shows progress bars to allow you to track the simulation’s activity. The “Log” option shows a transcript with detailed simulation output. Finally, the “Diagnostics” button supports generating on-the-fly diagnostic indicators.

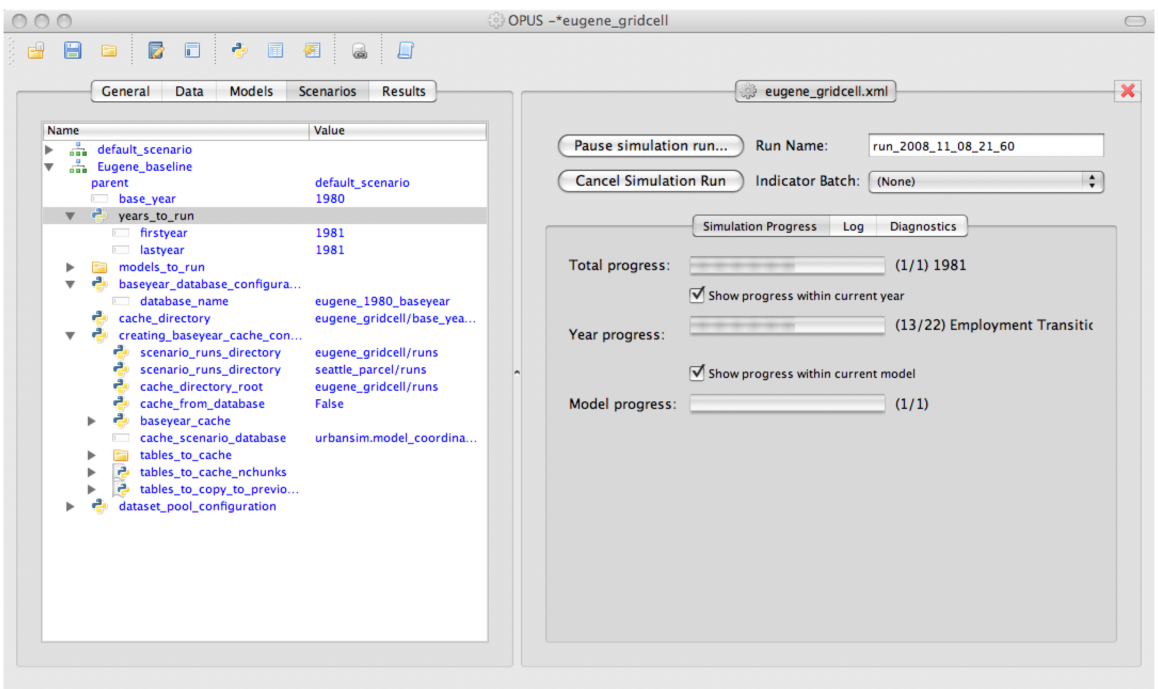


Figure 5.26: Running a simulation on Eugene baseline with all progress bars enabled

The default settings for “Simulation Progress” are to show the total progress in running the simulation, and the progress within the current year. For example, if you are running for 10 simulated years, when the first year is completed the progress bar for the current year will reach 100% and the total progress will reach 10%. You can hide the progress bar for the current year for a less cluttered display. Finally, if “Show progress within current year” is enabled, you have the additional option (off by default) to show progress within each model, such as Employment Transition, Household

Transition, and so forth. The currently running year, model, and chunk of model will be shown by the corresponding bars. Figure 5.26 shows a running simulation with all three progress bars enabled.

The “Log” option, as shown in Figure 5.27, shows the log output from running the same scenario. This can be monitored as the simulation runs, and also consulted after it has completed.

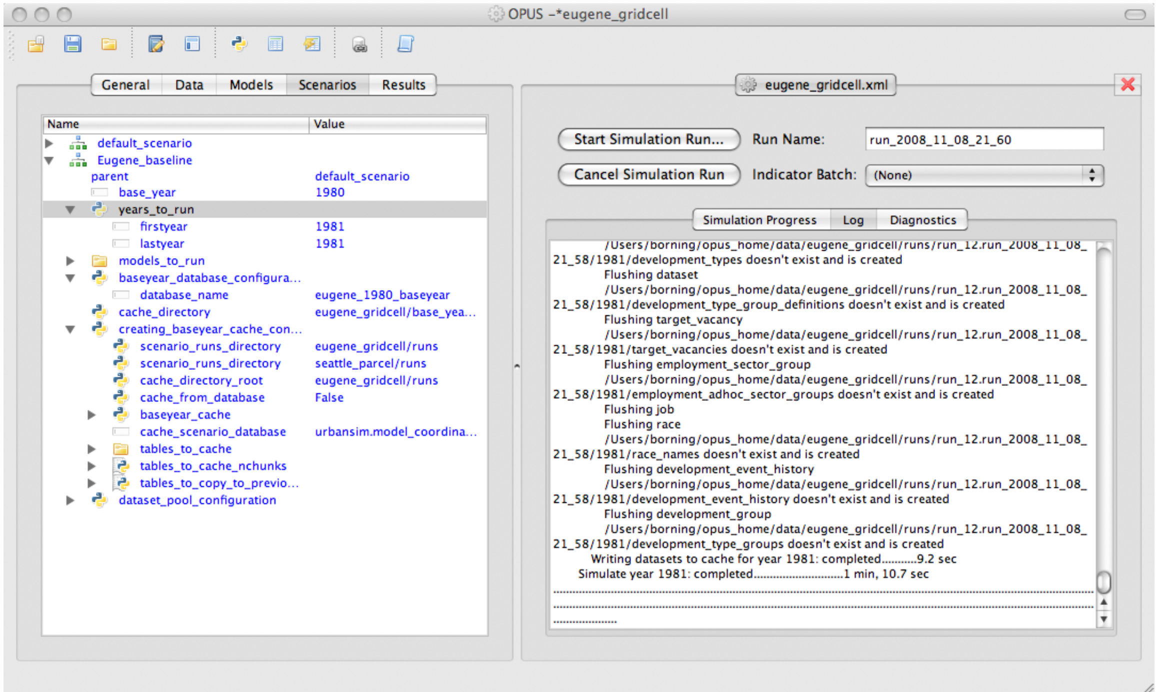


Figure 5.27: Log information from running a scenario

“Diagnostics,” the last of these three options, supports generating on-the-fly diagnostic indicators. If this option is selected, a series of combo boxes appears immediately below, allowing you to select a map or chart indicator, the level of geography, a specific indicator, and the year. As the given simulated year completes, the corresponding indicator visualization is shown underneath. For example, Figure 5.28 shows a diagnostic map of population for 1981 at the gridcell level for the Eugene baseline scenario.

Selecting and Configuring a Scenario

To select a scenario to run or configure its options, use the XML tree view on the left.

The default Eugene project contains only one scenario (“Eugene_baseline”). However, in general projects can contain multiple scenarios, all of which will be shown in the XML tree in the left-hand pane. Right-click on any one of them and select “Run this Scenario” to run.

To change any of the options in the XML tree you need to be able to edit it. The initial version of the Eugene_gridcell project in ‘opus_home/project_configs/eugene_gridcell_default.xml’ has basically no content of its own — everything is inherited from the default Eugene gridcell configuration in the source code. Inherited parts of the XML tree are shown in blue. These can’t be edited directly — they just show inherited information. Suppose that we want to change the last year of the simulation run from 1981 to 1990. To do this, first click on the triangle next to `years_to_run` in the XML tree. Right click on `lastyear` and select “Add to curent project.” This copies the inherited information into the local XML tree for the Eugene_gridcell configuration. The `lastyear` entry turns black, and you can now edit the year value to 1990. After the options are set up as you would like, you can then right click on the scenario and run it. Figure 5.29 shows the newly-edited scenario being run for 10 simulated years. (Notice that `lastyear` is now 1990 and shown in black.)

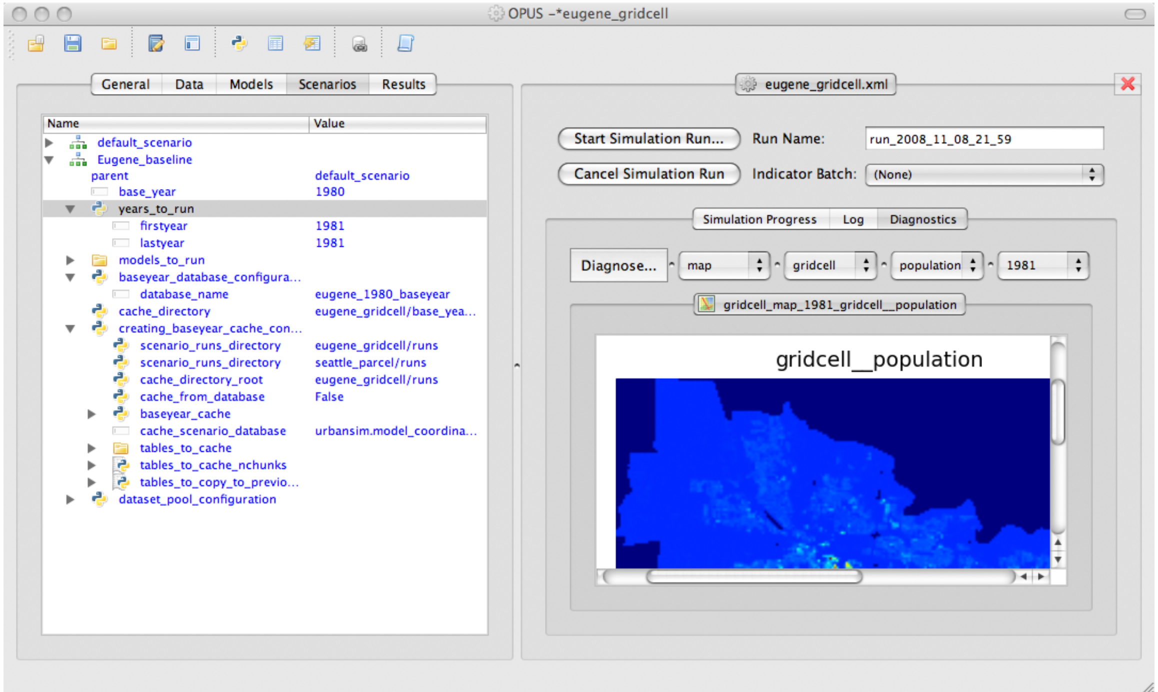


Figure 5.28: Using diagnostic indicators while running a scenario

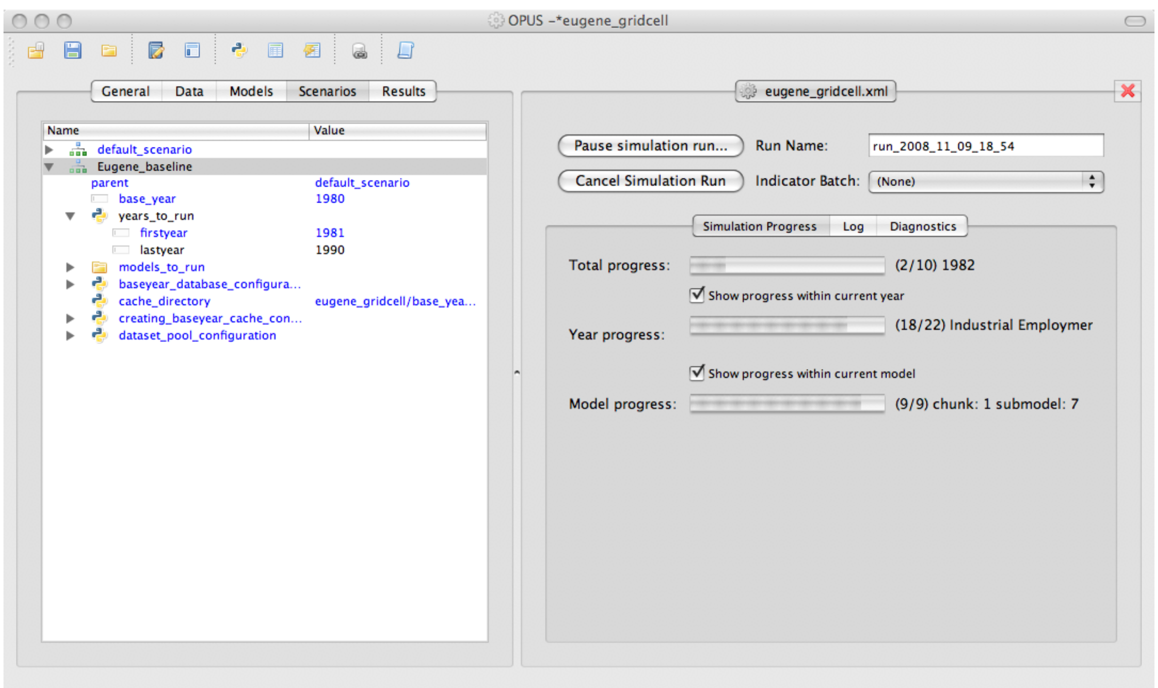


Figure 5.29: Running a scenario after changing the last year to 1990

The ending year of the scenario is the most likely thing that you'd want to change. Another possibility is to run only some of the component models. To do this, right-click on "Models to run," make it editable by selecting "Add to current project," and change the value of the "Run" field to "Skip" to skip that component model.

5.10 The Results Manager

The Results Manager, corresponding to the Results tab of the GUI, has two main responsibilities: to manage simulation runs for this project (Section 5.10.1) and to allow the interrogation of these simulation runs through the use of *indicators* (Section 5.10.2). We explore both of these in this chapter.

5.10.1 Managing simulation runs

The "Simulation runs" node captures all available simulation runs for this project. For example, when a simulation is run from the "Scenarios-manager" (see Section 5.9), an entry is made under "Simulation runs". If for some reason a run that you know exists for this project is not listed, right-click on "Simulation runs" and select "Import run from disk" (See Figure 5.30). The GUI will try to load the missing run and make it available.

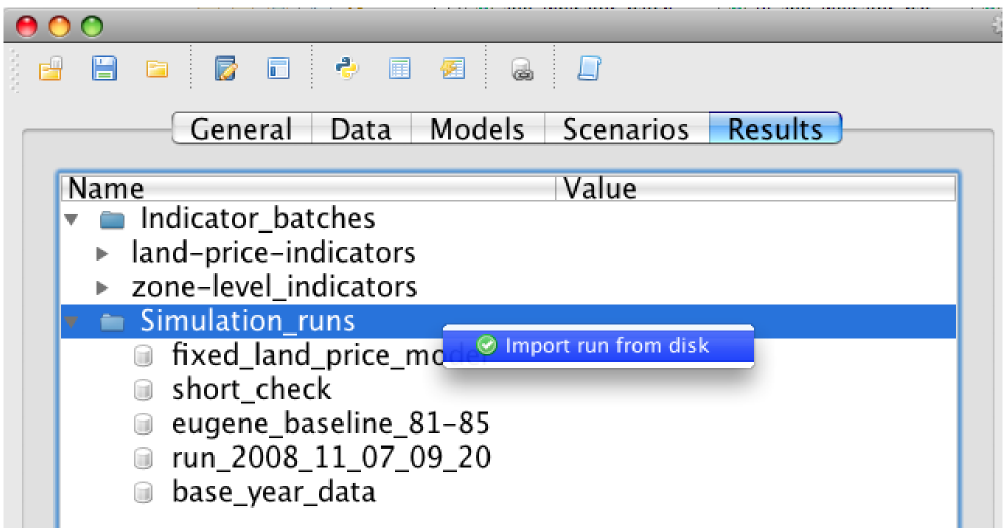


Figure 5.30: Importing a run from disk that is not showing up as a "Simulation run".

A couple operations can be performed on a simulation run. To view information about a given run, right-click on the run and select "Show details". To remove all traces of a simulation run, including the data on disk, right-click on the run and select "Remove run and delete from harddrive".

5.10.2 Interrogating Results with Indicators

Indicators are variables defined explicitly for use as a meaningful measure (see Section 5.4). Like model variables, they can be defined using the domain-specific programming language via the "Variable Library" accessible through the Tools menu (see Section 5.4). An indicator can then be visualized as either a map or as a table in a variety of formats. The GUI provides two ways to use indicators to understand what has happened in a simulation run: interactive result exploration (Section 5.10.2) and Batch indicator configuration and execution (Section 5.10.2).

Interactive result exploration

Often, it is desirable to explore simulation results in a lightweight fashion in order to get a basic idea of what happened. You don't necessarily want to go through the process of exporting results to a GIS mapping tool in order to gain some basic intuitions into spatial patterns.

The Opus GUI's "Result Browser", available from the "tools" menu, allows interactive exploration of simulation results. The Result Browser presents a selectable list of available simulation runs, years over which those simulations were run, and available indicators. You can then configure an indicator visualization by selecting a simulation run, a year, and an indicator. To compute and visualize the configured indicator, simply press the "generate results" button (See Figure 5.31). The indicator will then be computed for the year of the selected simulation run. After it is computed, a tab should appear at the bottom of the window with the name of the indicator. Subtabs allow you to see the results as a table or map (using the Matplotlib Python module).

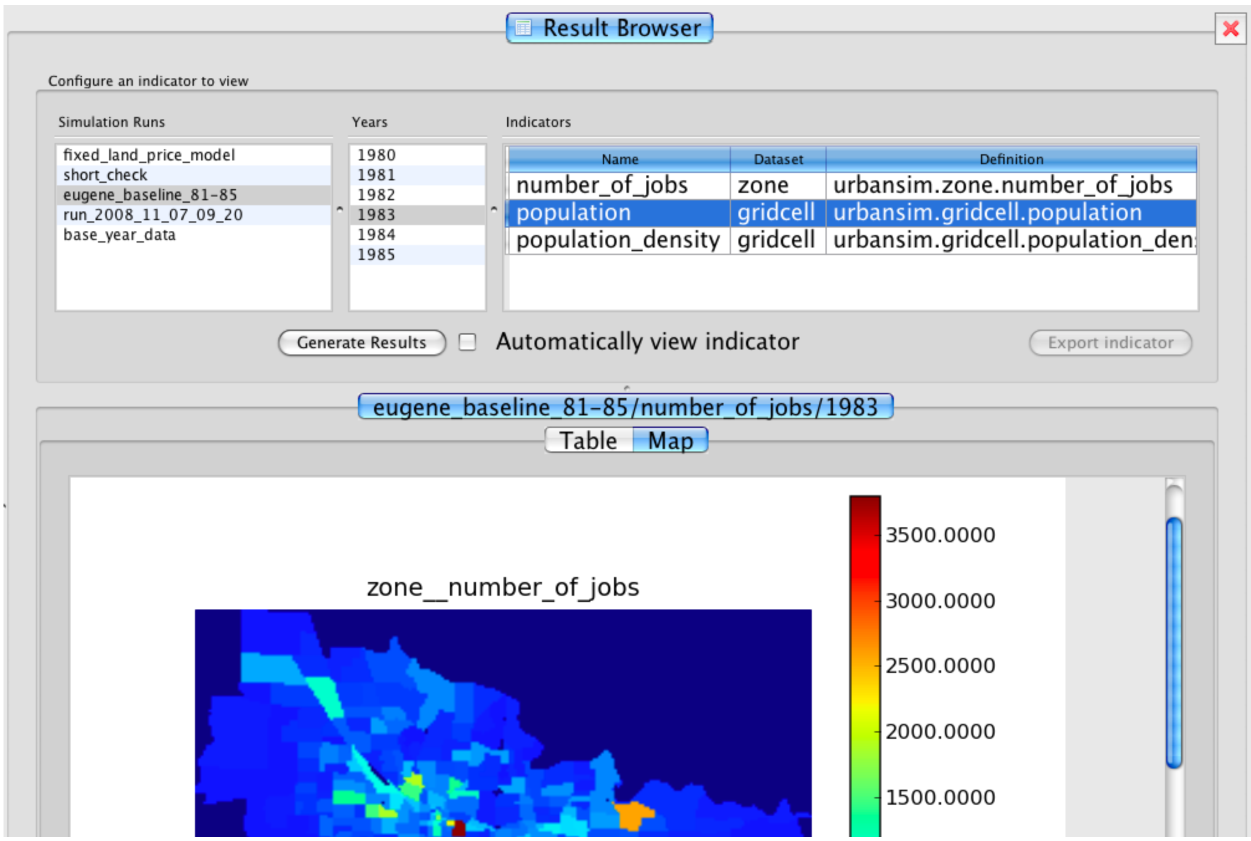


Figure 5.31: Using the "Result browser" for interactive result exploration.

1. Open the Results Browser from the Tools menu. Use the Results Browser to answer the following questions.
2. Just from visual inspection, is there more than one cluster of gridcells with high land value in the Eugene region in 1980 in the baseyear data?
3. Is this cluster(s) in the same general area as the greatest number of jobs in Eugene for the same year of the baseyear data?

Two additional aspects of the Result Browser should be mentioned:

1. If the checkbox "Automatically view indicator" is clicked, everytime you change the indicator configuration (i.e. select a different simulation run, year, or indicator), the indicator will be automatically visualized (as if you pressed the "Generate results" button).

2. The "Export results"button will export the table data of the currently configured indicator to a database. This feature is not yet implemented.

Batch indicator configuration and execution

The "Result Browser" is good for poking around in the data. But often you'll want to generate the same set of indicators for each of many runs and you don't want to redefine them every time. Instead, you'd like to configure and save a group of them that can be executed on demand on an arbitrary simulation run. In the Opus GUI, this functionality is supported with *indicator batches*.

To create a new indicator batch, right-click on the "Indicator_batches" node in the "Results tab" and select "Add new indicator batch..." (See Figure 5.32). A new batch will be created under the Indicator_batches node.

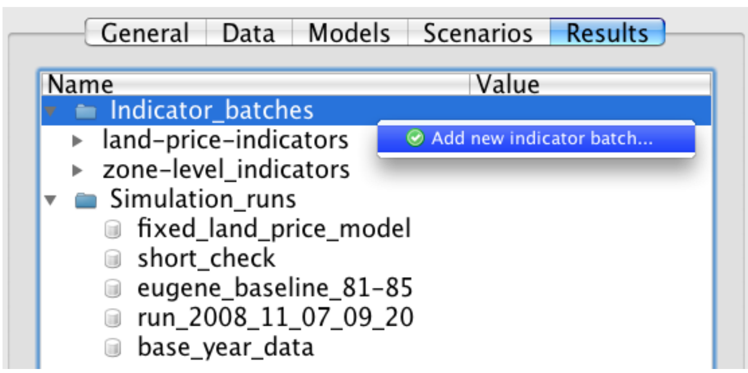


Figure 5.32: Creating a new indicator batch

A batch is a collection of "Indicator visualization" definitions. Each indicator visualization is a configuration of the indicator variable to be used, a visualization style (e.g. map or table), and some format options. To add a new indicator visualization to the batch, right-click on the respective batch and select "Add new indicator visualization…". A dialog box will appear where you can define the visualization. The visualization options for an indicator visualzation are discussed in depth later.

You can add as many indicator visualizations to a batch as you want. In order to execute an indicator batch on a simulation run, right-click on the indicator batch and hover over "Run indicator batch on…". A list of all the available simulations runs will appear as a submenu. You can then select the appropriate simulation. The indicator visualizations in the batch will be executed over all the years of that simulation run. If the resulting indicators are tables or maps stored in a file, they can then be found on disk in your "OPUSHOME/data/PROJECTNAME/runs/RUNNAME/indicators" directory, where "PROJECTNAME" is the name of your project (e.g. "eugene_gridcell") and "RUNNAME" is the name of the simulation run that you selected to run the batch on. The indicator visualizations configured to write to a database will have produced tables in the specified database with the name of the respective indicator visualization.

Create, configure, and execute a new indicator batch:

1. Create a new indicator batch by right-clicking on the "Indicator_batches" node in the Results tab and selecting the appropriate option.

2. Add an indicator visualization configuration to that batch. Right-click on your new indicator batch and select "Add new indicator visualization".

3. Configure a Map visualization that contains the zone_job_density and zone_population_density indicators for the zone dataset.

4. Close the batch visualization configure dialog.

5. Right-click on the batch and execute your indicator batch on the results of a simulation run.

Indicator visualization configuration options

Opus provides a variety of ways to visualize indicators and this functionality is exposed in the "Indicator visualization" dialog box options (e.g. multi-year indicators, exporting to databases). This section describes the range of available options in the Batch indicator visualization dialog box, which is separated into three components: "indicator selection", "output options", and "format options" (See Figure 5.33).

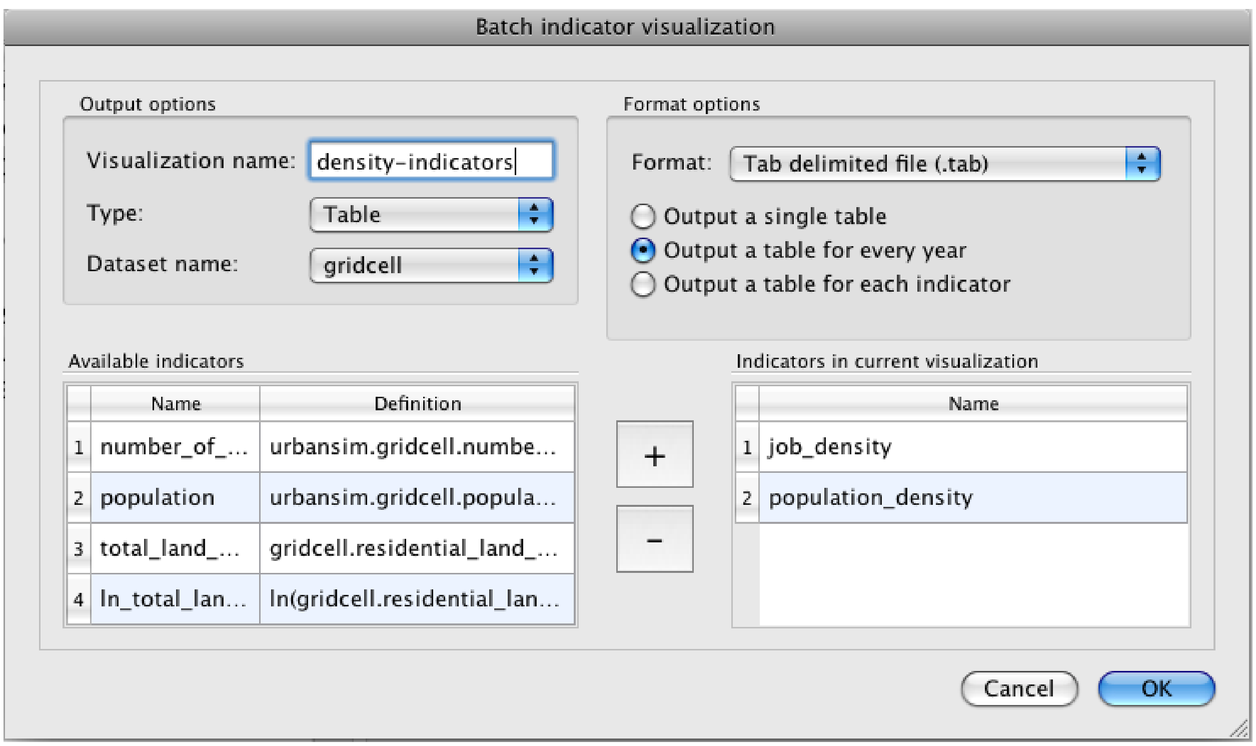


Figure 5.33: The batch visualization creation dialog.

Indicator selection

The bottom of the dialog box has two list boxes, "available indicators" and "indicators in current visualization". The indicators here are those variables defined in the "Variable Library" (see Section 5.4) whose *use* has been set to be *indicator* or *both*. Note that the set of indicators available is filtered by the currently selected dataset in the "output options" (described later in this section).

By moving an indicator from the "available indicators" box to the "indicators in current visualization" bo via the "+" button, you include that indicator in this indicator visualization. Likewise, to remove an indicator from the visualization, select the indicator in the "indicators in current visualization" box and press the "-" button.

Output options

Visualization Name. The base name of any produced visualizations. Because you might be producing this visualization for different years and different simulation data, more information will be appended to this name to ensure uniqueness of the resulting file or database table when the visualization is run on some data.

Type. There are two different types of indicator visualizations that can be produced: maps and tables. Tables are just raw data organized into rows and columns, while maps are spatial projections of this data. The available format options (described later) are fully dependent on the visualization type.

Dataset name. The dataset that this visualization corresponds to. When the selected indicator(s) are run, they will be computed over this dataset. Most commonly you are choosing a geographic granularity (e.g. gridcell, zone) that you want to see the results at. Note that when you change the dataset, the set of available indicators changes because a given indicator is valid only for a single dataset.

Format options for maps

Map visualizations will produce a map file for every selected indicator for every available year when it is executed on a simulation run.

The available map format is Mapnik, an open-source toolkit for developing mapping applications (`http://mapnik.org/`). Note that the Mapnik maps are not intended to replace GIS-based mapping, which allows far more control and the overlay of other features for visual reference. It is merely a quick tool to visualize data to get a sense of the spatial patterns in it. In order to support visualization in a GIS environment such as ArcGIS or QGIS, the results may be exported to a database or geodatabase environment, and the GIS software used to create a more interactive and flexible display of the data. See the following section for a description of how to export indicator results to a SQL database or a DBF file for use in external GIS tools.

Export the results that were found in the previous tutorial inset to a SQL database.

1. Make sure that you have configured a database server. From the Tools menu, select "Database Server Connections". Check to see that the "indicators_database_server" is correctly set up. If you don't have a remote database server, make sure that it points to a sqlite connection. Close the connections dialog box.

2. Reconfigure the batch to write to a database. Expand the indicator batch that you defined in the prior step. Right-click on the visualization and select "Configure visualization". Change the format to "Export to SQL database" and then name a database it should write to. Hit OK and then rerun the batch on the simulation results from before.

3. Launch a database browser and check to see if the proper tables were created.

To set the Mapnik map options, first open the batch visualization creation dialog window (shown above) by clicking on the Results tab, right-clicking "Indicator_batches", selecting the "Add new indicator batch…" option, right-clicking the new indicator batch, and selecting the "Add new indicator visualization…" option. Select "Map" from the "Type:" drop-down menu, then click the "Mapnik Map Options" button that will appear directly below the "Format:" drop-down menu. In the Mapnik Map Options dialog window, there are two tabs where all of the mapping options can be set: Legend Options and Size Options.

Legend Options tab:

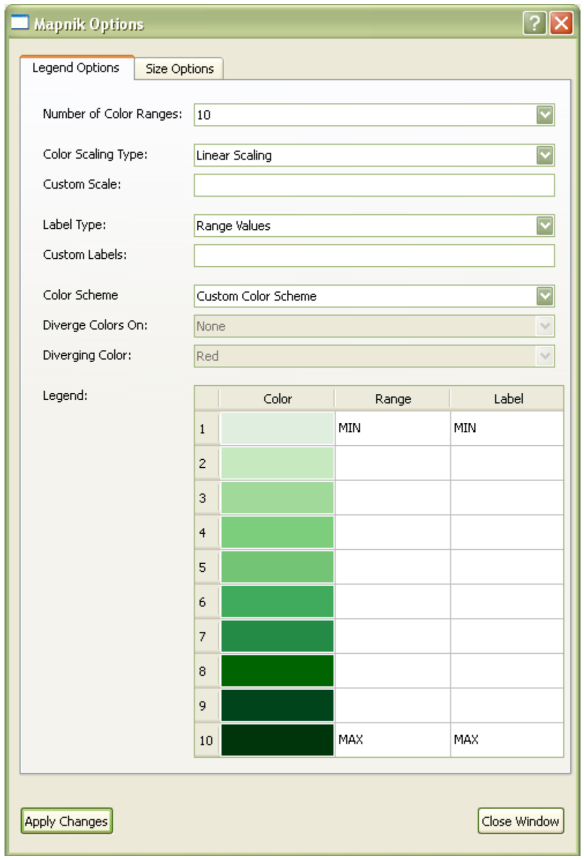


Figure 5.34: The map options dialog window showing default settings (Legend Options).

Number of Color Ranges. This sets the number of buckets to split the range of the values being mapped in to. The drop-down menu allows you to choose a number between 1 and 10.

Color Scaling Type. This drop-down menu allows you to choose between "Linear Scaling", "Custom Scaling", "Custom Linear Scaling", and "Equal Percentage Scaling". Linear scaling will evenly divide of the range of values to be mapped into buckets of the same size. Custom scaling will let you specify how to divide the range of values into the buckets. Custom linear scaling will let you specify a minimum and maximum value and then will evenly divide the range of values into buckets of the same size. Equal Percentage Scaling will divide the range of values up so that (100/number of buckets) percent of the values fall into each category.

Custom Scale. If "Custom Scaling" is selected as the Color Scaling Type, then the values in this text field will be used to define the bucket ranges. For example, if the following string is entered in the Custom Scale text field "5, 100, 2000, 40000", then the bucket ranges will be '5 to 100', '100 to 2000', and '2000 to 40000'. Also, if either "min", "MIN", "max", or "MAX" is entered in the Custom Scale text field, they will be replaced with the minimum or maximum values of the values that are being mapped. For example, "min,100,max" is a valid entry for Custom Scale.

Label Type. This drop-down menu allows you to choose between "Range Values" and "Custom Labels" to use as the labels on the color bar that will be drawn in to the map image. Using range values means that the boxes in the color bar will be labeled with the range of values that are being colored with the color contained in the corresponding box. Using custom labels allows you to manually enter the labels for each box.

Custom Labels. If "Custom Labels" is selected as the Label Type, then the values in this text field will be used to label the colored boxes in the color bar. For example, if the following string is entered in the Custom Labels text field "a,b,c,", then the first box will be labeled "a", the second will be labeled "b", and the third will be labeled "c".

Color Scheme. This drop-down menu allows you to choose between "Custom Color Scheme", "Green", "Blue", "Red", and "Custom Graduated Colors". The color buttons in the legend are buttons, that when pushed, cause a color chooser dialog window to pop up that can be used to pick the color of the box. If Custom Color Scheme is selected, then all manually-set colors will be saved when the "Apply Changes" button is pushed, whereas all colors will be over-written when the "Apply Changes" button is clicked if any other color scheme option is selected. If Green, Blue, or Red is selected, the boxes will be colored with pre-defined colors. Lastly, if Custom Graduated Colors is selected, then the boxes will be colored in an even, graduated scale where the range of colors starts at the current color of the box at index 1 and ends at the current color of the box at the highest index.

Diverge Colors On. This gives you the option to have two diverging colors. You have to option "None" to split on none of the indices to use just one color scale, or you have the option to split on any index from 1 to 10. The color box at the selected index will be set to white and the two color scales above and below it will be set based on what color option is selected in the Color Scheme and Diverging Color drop-down menus. Note that if "Custom Graduated Colors" is selected in the Color Scheme drop-down menu, then the two color scales above and below the box at the diverging index will have graduated color scales and the option selected in the Diverging Color drop-down menu will be ignored.

Diverging Color. This drop-down menu allows you to choose between "Red", "Green", and "Blue". This will set the color for the boxes with an index number lower than the index number selected in the Diverge Colors On drop-down menu. Note: any selection made in this menu will be ignored if "Custom Color Scheme" is selected in the Color Scheme drop-down menu.

Legend. The legend has three columns: Color, Range, and Label. The Color column has color boxes that display the color currently selected for the corresponding color bucket. Also, clicking a color box will bring up a dialog window that will allow you to select a custom color to display on the color box. The Range column has numerical values that define the range of the corresponding color bucket and these values can be edited within the legend table if "Custom Scaling" is selected in the Color Scaling Type drop-down menu. The Label column has the label that will be applied to each color bucket on the color bar that will be included in the map. These values are editable from within the legend table if "Custom Labels" is selected in the Label Type drop-down menu. Note: values entered in the legend table will only be saved correctly if they appear correctly in the Custom Scale and Custom Labels text fields.

Size Options tab:

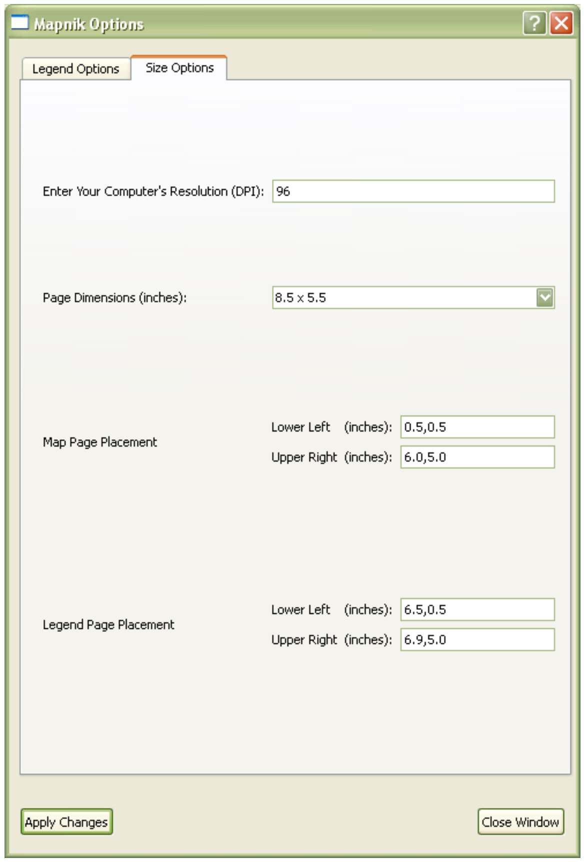


Figure 5.35: The map options dialog window showing default settings (Size Options).

Enter Your Computer's Resolution (DPI). This value is used to convert from inch measurements to pixel measurements (pixels = inches x DPI). The resolution for the computer that the map is being created on should be entered here.

Page Dimensions (inches). Available dimensions for the map image file (map and legend) are listed here in the drop-down menu.

Map Page Placement. Lower left and upper right coordinates for a bounding box on the map image can be entered here. The map image will be placed in the center of the given bounding box and will only be drawn as large as possible without being stretched or skewed. Coordinates should be entered in the form "x,y" and the coordinate (0,0) is at the lower left corner.

Legend Page Placement. Lower left and upper right coordinates for the color bar of the legend can be entered here. The color bar will fill the area defined by the given coordinates and then the labels will be drawn to the right of the color bar.

Mapnik Options Window Buttons:

Apply Changes. This will save the current settings to the project XML file as well as update the Legend showing in this window.

Close Window. This will close the options window and discard any unsaved settings.

Examples of how to create default and custom maps

Create a default map. To create a map with the default settings (using the Eugene gridcell project), create an indicator batch and in the batch indicator visualization dialog window, set Type to "Map", set Dataset name to "zone", and select "number_of_jobs" to be included in the current visualization. Then run the indicator batch on a simulation by right-clicking the indicator batch in the results tab and selecting "Run indicator batch on…". This will produce a map with the default settings of 10 color ranges, colored green, where each color range is the same size and linearly increasing from light green to dark green. For more instructions on how to create and run an indicator batch see section 5.10.2. The map will look like the map shown below.

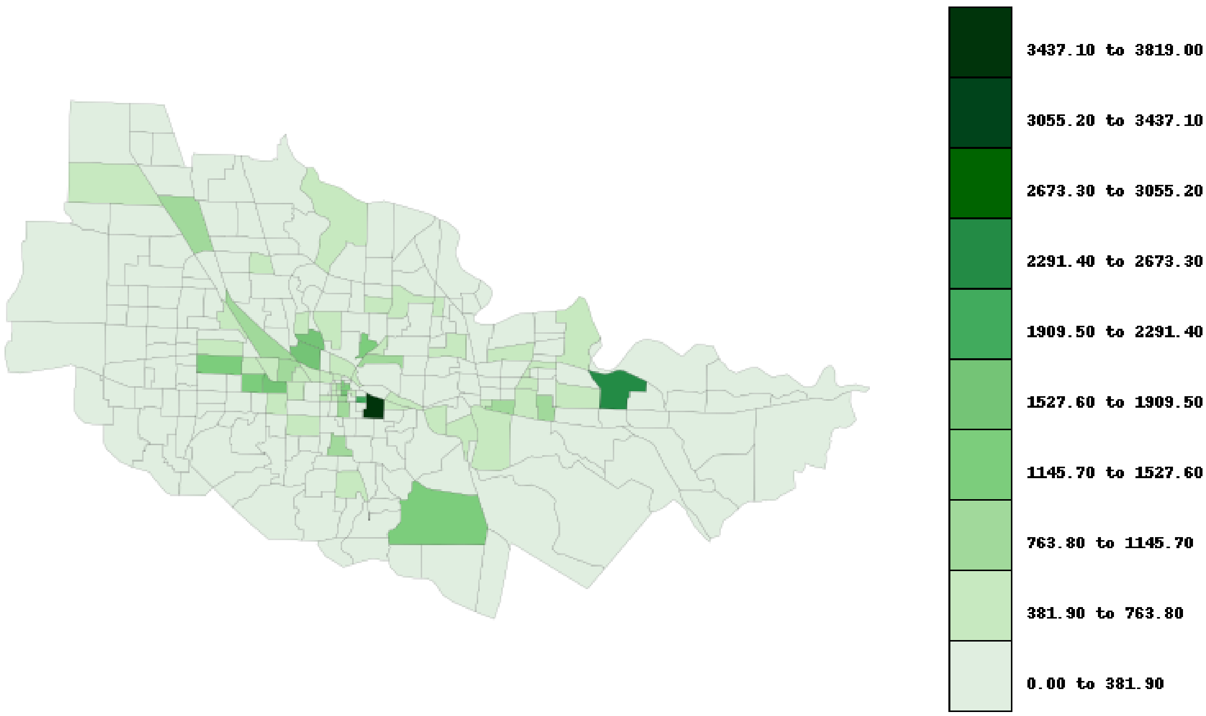


Figure 5.36: A Mapnik map colored with the default color scheme.

Create a custom map. To create a customized map, open the batch indicator visualization window (see section 5.10.2 on batch indicator configuration for information on how to do this), for the map created in the *Create a default map* section and click on the Mapnik Map Options button that is directly below the Format drop-down menu.

Suppose that we would like to create the same map again, but this time with 9 color ranges, custom ranges, custom labels, and a diverging color scheme where all values from 0 to 300 are colored with gradually lighter shades of blue and all values from 300 to 4000 are colored with gradually darker shades of red. As a side note, the option to use a diverging color scheme exists primarily to allow the coloring scheme to differentiate between positive and negative values. However, all values in this example are all greater than or equal to zero.

Select “9” in the Number of Color Ranges drop-down menu, select “Custom Scaling” in the Color Scaling Type menu, enter “0,50,100,150,200,300,400,500,1000,4000” in the Custom Scale text field, select “Custom Labels” in the Label Type menu, enter “a,b,c,d,e,f,g,h,i” in the Custom Labels text field, select “Red” in the Color Scheme menu, select “6” in the Diverge Colors On menu, select “Blue” in the Diverging Color menu, and the press the Apply Changes button.

The color box at the index specified in the Diverge Colors On menu will be set to white. This color can be changed to a light pink color by clicking on the color box in the row specified in the Diverge Colors On menu to bring up a dialog window that lets you choose a new color. From the color chooser dialog window, select a light pink color and press OK. Check to make sure the selected option in the Color Scheme menu has been changed to “Custom Color Scheme” so that your custom color for the color box in row 6 will be saved when the Apply Changes button is pressed, and then press the Apply Changes button. If “Custom Color Scheme” is not selected, then when the Apply Changes button is pressed, all colors will be reset based on the color scheme options that is currently selected. The mapnik options dialog window should look like the screenshot pictured below. The map that will be created after the indicator batch has been run is also shown below. (see section 5.10.2 for information on how to run an indicator batch)

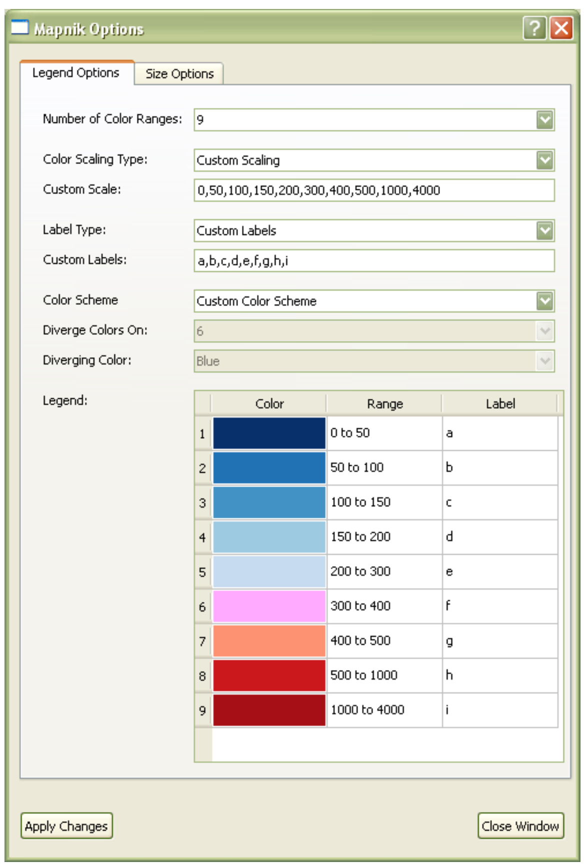


Figure 5.37: The Mapnik map options window showing custom settings.

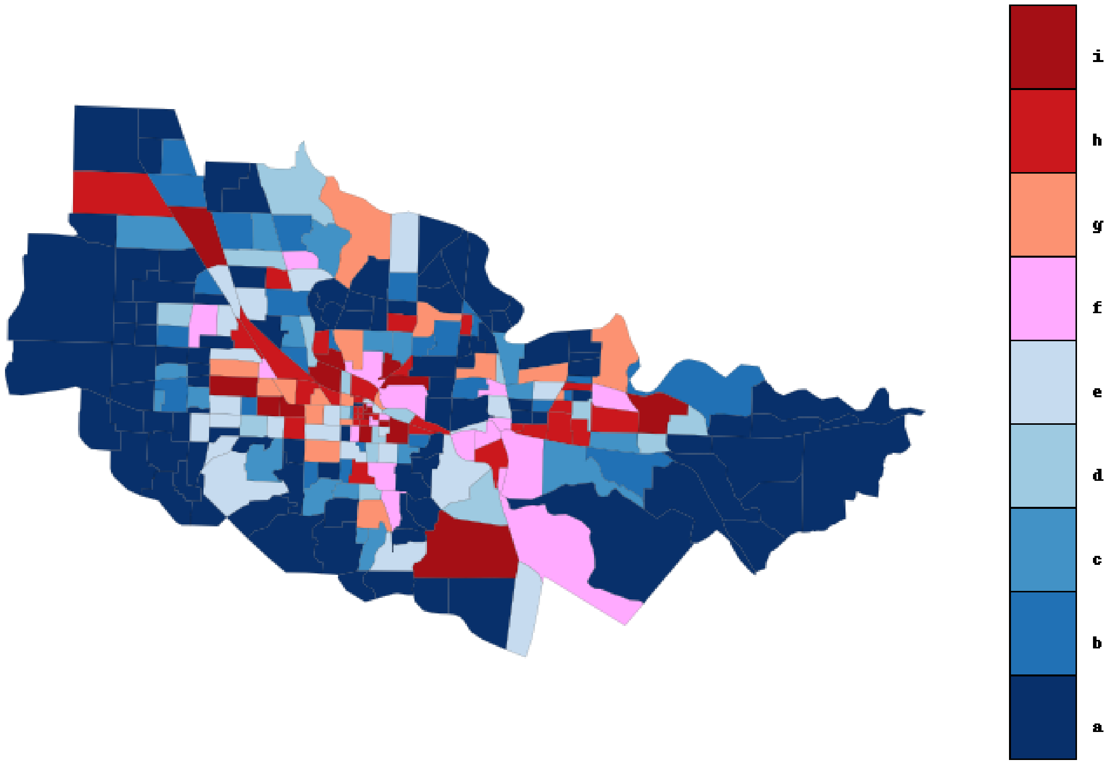


Figure 5.38: A Mapnik map with a custom color scheme.

Create a custom graduated color scheme. To create a map with a custom graduated color scale, re-open the Mapnik Options dialog window for the map created in the *Create a custom map* section. Click on the box in row 1 and select a light shade yellow, click on the box in row 9 and select a bright shade of blue, select "Custom Graduated Colors" from the Color Scheme menu, and click Apply Changes. The colors in boxes 2 through 8 will then be automatically set to create a graduated color scheme that spans from light yellow to bright blue. The mapnik options window and resulting map are shown below. (see section 5.10.2 for information on how to run an indicator batch)

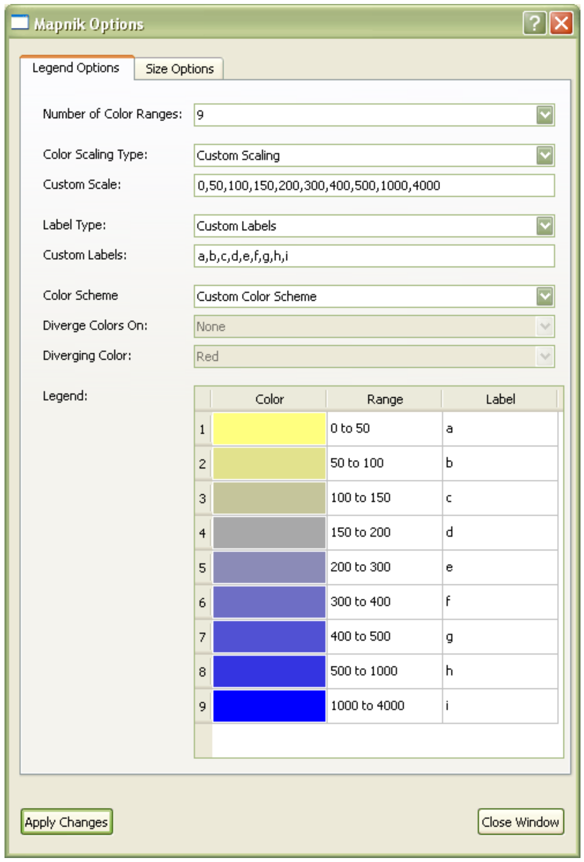


Figure 5.39: The Mapnik map options window showing a custom graduated color scheme.

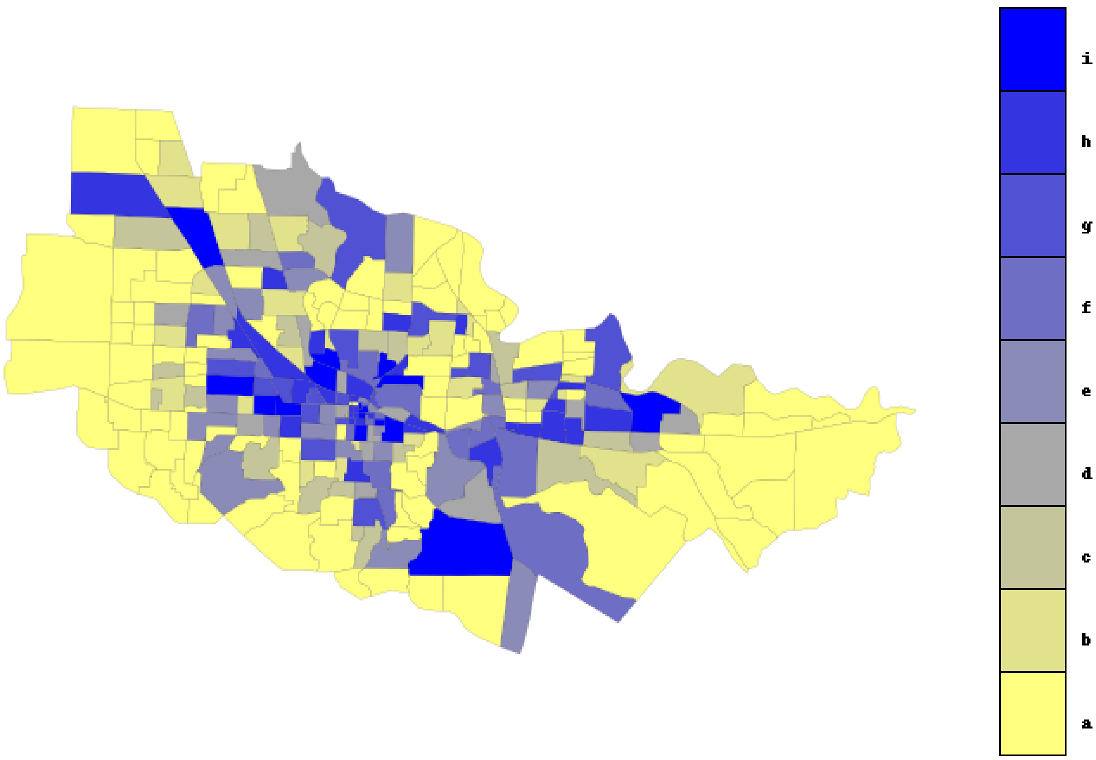


Figure 5.40: A Mapnik map with a custom graduated color scheme.

Create a diverging custom graduated color scheme. The graduated color schemes can also diverge on an index. Shown below is the Mapnik options dialog window with the same settings as set in the *Create a custom graduated color scheme* section, but the selected option in the Diverge Colors On has been changed from "None" to "5".

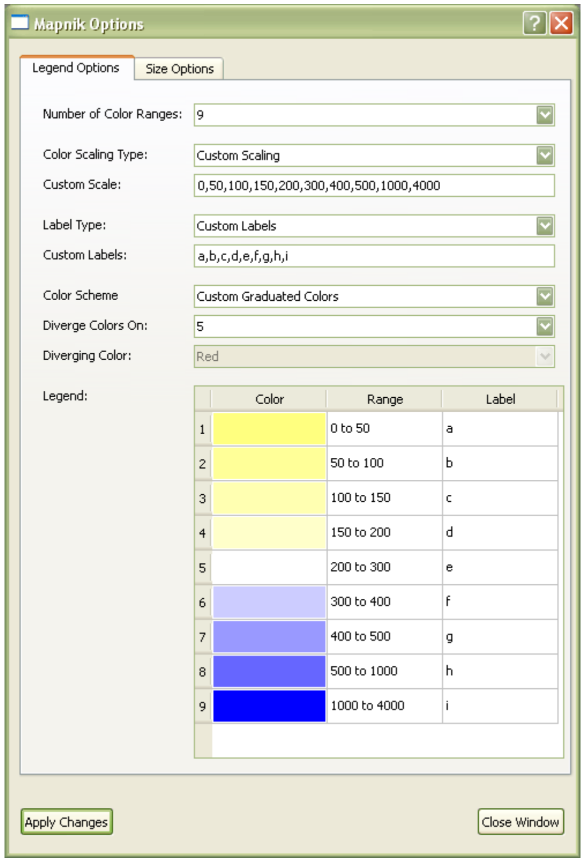


Figure 5.41: The Mapnik map options window showing a diverging custom graduated color scheme.

Create a map with attributes that are True/False values. To create a map with attributes that are True/False values rather than numerical values (using the Seattle parcel project), create an indicator batch in the batch indicator visualization dialog window, set Type to "Map", set Dataset name to "parcel", and select "hwy2000" to be included in the current visualization. (See Section /refsec:variable-library for information on how to use the "Variable Library" to add hwy2000 to the list of available indicators.) Then click the Mapnik Map Options button that is directly below the Format drop-down menu.

In the Mapnik Options dialog window, set the options as shown in the figure below. Number of Color Ranges: "2", Color Scaling Type: "Custom Linear Scaling", Custom Scale: "0,1", Label Type: "Custom Labels", Custom Labels: "False,True", Color Scheme: "Custom Color Scheme". Lastly, in the legend, click the color box in row 1 to set the color to red and click the color box in row 2 to set the color to blue. Press the apply changes button to save these settings. The map that will be created after the indicator batch has been run is also shown below. (see section 5.10.2 for information on how to run an indicator batch)

Note: The scale is "0,1" because 'False' and 'True' are numerically represented as '0' and '1' respectively.

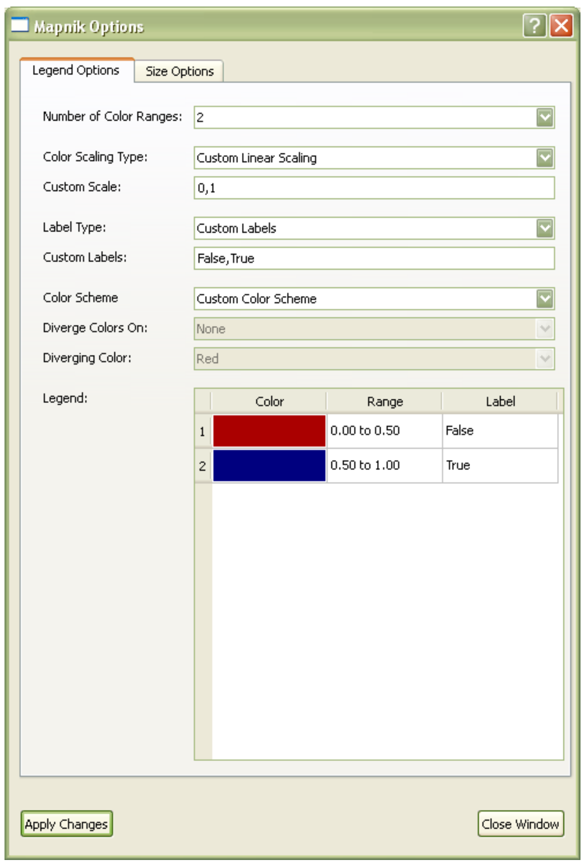


Figure 5.42: The Mapnik map options window showing settings for a True/False map.

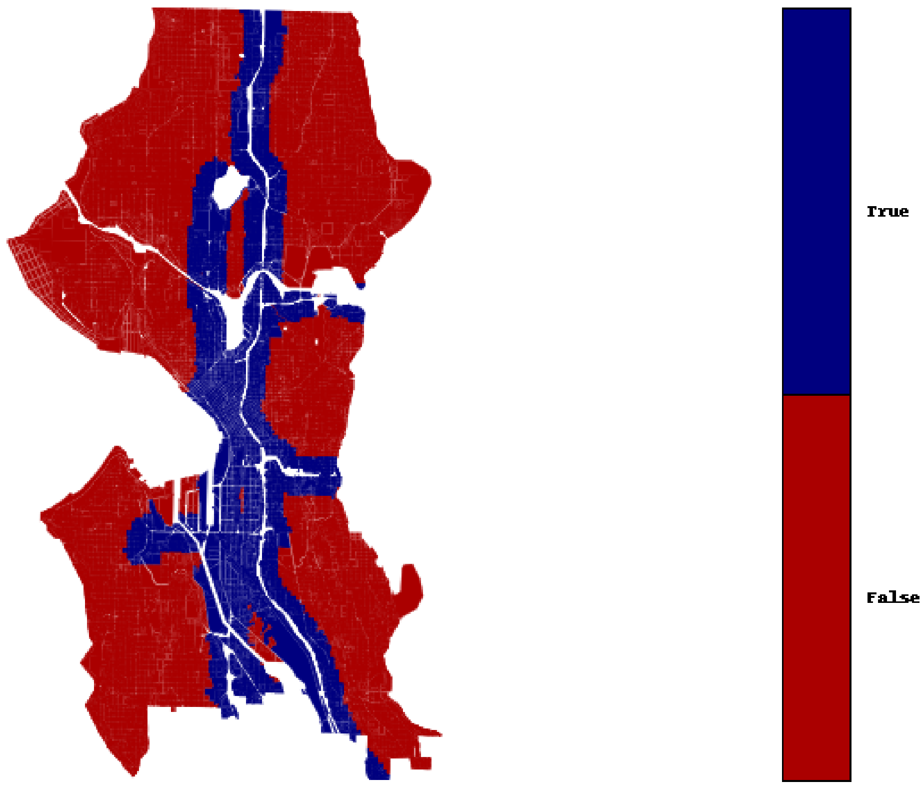


Figure 5.43: A Mapnik map showing a map with True/False attributes.

Format options for animations

Animation visualizations will produce an animation file for every selected indicator that repeatedly loops through map images that correspond to the years the batch was selected to run on when it is executed on a simulation run.

The available animation format is Mapnik, an open-source toolkit for developing mapping applications (`http://mapnik.org/`).

To set the Mapnik map options, first open the batch visualization creation dialog window by clicking on the Results tab, right-clicking "Indicator_batches", selecting the "Add new indicator batch..." option, right-clicking the new indicator batch, and selecting the "Add new indicator visualization..." option. Select "Animation" from the "Type:" drop-down menu, then click the "Mapnik Map Options" button that will appear directly below the "Format:" drop-down menu. In the Mapnik Map Options dialog window, all of the animation options can be set.

All of the animated map options are the same as the non-animated map options. See the above section on format options for maps for more info.

Format options for tables

There are four different available formats for tables. Each has its own parameters that need to be set. Note that the id column for the dataset will automatically be included in all outputted tables regardless of format.

Tab-delimited (.tab). This will output a file (or multiple files) where the values are separated by tabs. There are three different modes to choose from that affects how data is split across files when the visualization is executed on a simulation run. "Output in a single file" will create single tab file that has a column for each selected indicator for each year of the simulation run. "Output in a table for every year" will create a tab file for each year of the simulation run, with each column corresponding to a selected indicator. Finally, "Output a table for each indicator" will create a tab file for each selected indicator, where each column corresponds to the indicator values of a year of the simulation run.

Fixed-field. The fixed field format will output a single file whose fields are written with fixed width and no delimiters. The file contains a column for each selected indicator for each year of the simulation run for which the visualization is being created. Format info for each column needs to be specified. To specify the format of the dataset id column, fill in the "id_col" input field. To specify the format of each selected indicator, enter the format in the respective row of the "field format" column in the "indicators in current visualization" box. The field format has two parts, the length of the field and the type. Available types are float ("f") and integer ("i"). Specified field formats follow the pattern "10i" and "5.2f", where the latter specifies a float with five leading digits with floating point precision carried out to two decimal places.

SQL database. This format option can be used to export to an arbitrary SQL database. The database server used is that specified in the "Database server connections" under "indicators_database" (see Section 5.5.3). The exported data will take the form of a newly created in the specified database (if the database doesn't exist, it will be created first). The SQL table will contain a column for every selected indicator for every year of the simulation run that it is being executed against. The name of the table is a combination of the name of the visualization and the name of the simulation run. Additionally, if you are exporting to a PostGRES database and have an existing spatial table corresponding to the dataset of the visualization, a view defining a join over the spatial table and the indicator table will automatically be created. This allows you to instantly view the indicator results in QGIS.

ESRI database. This option exports the indicator data to an ESRI database that can be loaded into ArcMap. Simply specify the path to a geodatabase file (.gdb). It is assumed that the geodatabase contains a `Feature Class` corresponding to the dataset of the indicator being exported. Once the export is successfully completed, the geodatabase will contain a table that contains the indicator result, with a zone_id and an ArcGIS `OBJECTID*` that corresponds to the internal object ids in the feature class. It is safe to join the indicator table result with the feature class using either the objectid or the zone_id. See Figure 5.44 for an example exported indicator after following this process.

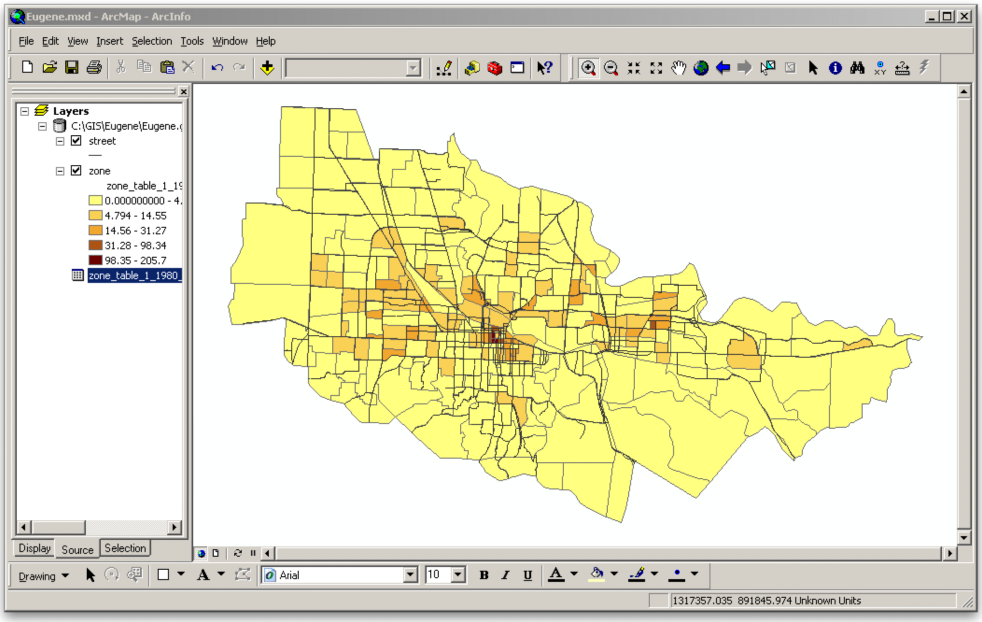


Figure 5.44: Mapping a Population by Zone Indicator in ESRI ArcMap. Shows the result of joining the feature class with the indicator table and generating a thematic map of the populaion by zone, using the zone.acres field to normalize the population, resulting in a map of population density per acre.

5.11 Inheriting XML Project Configuration Information

As previously discussed, Opus uses XML-based configuration files to flexibly specify the various aspects of a project, as well as to specify the appearance of the different tabs in the GUI.

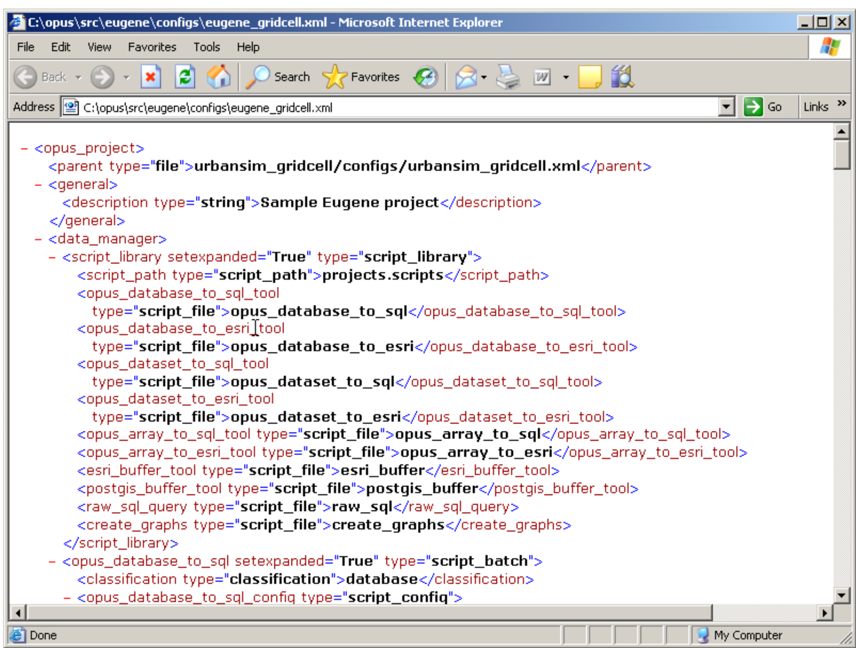
One configuration (the *child*) can inherit from another configuration (the *parent*). By default, the child inherits all the information contained in the project. However, it can override any information inherited from the parent, and add additional information. This means that you can use default projects as parents for another project you want to create that is mostly the same as an existing project, but has some changes from it. An XML configuration specifies its parent using the *parent* entry under the "General" section of the XML. The value of this is the name of the XML file that contains the parent configuration. When searching for this file, Opus first looks in the same directory that holds the child configuration. If it's not found there, it expects to find a path in the Opus source code tree, starting with the name of a project like eugene or urbansim.

This works well with the convention that users should create their own projects in the 'opus/project_configs' directory. You can have several configurations in your 'opus/project_configs' directory, one inheriting from the other. Ultimately, though, one or more of these configurations should inherit from a default configuration in the source code tree in 'opus/src'. For example, Figure 5.45 shows the contents of the 'eugene_gridcell_default.xml' project in 'opus/project_configs'. This has almost no content of its own, but rather inherits everything but the description from the parent configuration in the source code tree at 'eugene/configs/eugene_gridcell.xml'.

A small section of its parent, 'eugene/configs/eugene_gridcell.xml', is shown in Figure 5.46. This is just a text file, but in a structured format, with nodes corresponding to information that is displayed in the GUI. Some of the content of the XML provide data used by the GUI to determine how to display information, or what menu items are appropriate to connect to the node in the GUI. Notice that this project in turn inherits from 'urbansim_gridcell/configs/urbansim_gridcell.xml'.

```
<opus_project>
  <xml_version>4.2.0</xml_version>
  <general>
    <description type="string">Minimal user configuration for the Eugene gridcell project</descrip
    <parent type="file">eugene/configs/eugene_gridcell.xml</parent>
  </general>
</opus_project>
```

Figure 5.45: Contents of the default eugene_gridcell.xml project



```
- <opus_project>
    <parent type="file">urbansim_gridcell/configs/urbansim_gridcell.xml</parent>
  - <general>
      <description type="string">Sample Eugene project</description>
    </general>
  - <data_manager>
    - <script_library setexpanded="True" type="script_library">
        <script_path type="script_path">projects.scripts</script_path>
        <opus_database_to_sql_tool
          type="script_file">opus_database_to_sql</opus_database_to_sql_tool>
        <opus_database_to_esri_tool
          type="script_file">opus_database_to_esri</opus_database_to_esri_tool>
        <opus_dataset_to_sql_tool
          type="script_file">opus_dataset_to_sql</opus_dataset_to_sql_tool>
        <opus_dataset_to_esri_tool
          type="script_file">opus_dataset_to_esri</opus_dataset_to_esri_tool>
        <opus_array_to_sql_tool type="script_file">opus_array_to_sql</opus_array_to_sql_tool>
        <opus_array_to_esri_tool type="script_file">opus_array_to_esri</opus_array_to_esri_tool>
        <esri_buffer_tool type="script_file">esri_buffer</esri_buffer_tool>
        <postgis_buffer_tool type="script_file">postgis_buffer</postgis_buffer_tool>
        <raw_sql_query type="script_file">raw_sql</raw_sql_query>
        <create_graphs type="script_file">create_graphs</create_graphs>
      </script_library>
    - <opus_database_to_sql setexpanded="True" type="script_batch">
        <classification type="classification">database</classification>
      - <opus_database_to_sql_config type="script_config">
```

Figure 5.46: An Excerpt from eugene/configs/eugene_gridcell.xml

To change any of the options in the XML tree you need to be able to edit it. Inherited parts of the XML tree are shown in blue in the left pane in the GUI. These can't be edited directly — they just show inherited information. You can make an inherited portion of the XML tree editable by right clicking on it and selecting "Add to curent project." This copies the inherited information into the local XML tree, which then is shown in black. We saw an example of doing this in Section 5.9.1. Figure 5.29 in that same section shows an XML tree that is mostly inherited (and so shown in blue).

A few details about the "Add to current project" command: in Section 5.9.1, when we added `lastyear` to the current project, the containing nodes in the tree (`years_to_run` and `Eugene_baseline`) also turned black, since they needed to be added to the current project as well to hold `lastyear`. It's also possible to click directly on `years_to_run`, or even `Eugene_baseline`, and add the XML tree under that to the current project. However, we recommend adding just the part you're editing to the current project, and not others. (You can always add other parts later.) The reason is that once a part of the tree is added to the current project, the inheritance relation of that part with the parent disappears, and changes to the parent won't be reflected in the child XML. For example, if you add all of the `Eugene_baseline` node to the current project, save your configuration, and then update the source code, changes to some obscure advanced feature in the XML in the parent in the source tree wouldn't show up in your configuration.

When you first start up the GUI and open a project, we suggested starting with the default 'eugene_gridcell_default.xml' configuration. You can use the "Save as" command to save it under a new file name, and in that way keep multiple configurations in your 'opus/project_configs' directory. You can change the parent of a configuration by editing its parent field under the "General" tab — if you do this, save the configuration and then re-open it so that the GUI will read in the new parent information (it currently doesn't do that automatically). Finally, since configurations are just files, you can copy them, save them on a backup directory, or email them as attachments to other users. (You can also edit them directly with a text editor — but only do this if you know what you're doing, since there won't be any checks that after your edits the configuration is still well-formed.)

BIBLIOGRAPHY

Ben-Akiva, M. & Lerman, S. R. (1987), *Discrete Choice Analysis: Theory and Application to Travel Demand*, The MIT Press, Cambridge, Massachusetts.

Clark, W. A. V. & Lierop, W. F. J. V. (1986), Residential mobility and household location modeling, *in* 'Handbook of Regional and Urban Economics, Volume 1', Elsevier Science Publishers BV, pp. 97–132.

DiPasquale, D. & Wheaton, W. (1996), *Urban Economics and Real Estate Markets*, Prentice Hall: Englewood Cliffs, NJ.

Greene, W. H. (2002), *Econometric Analysis*, 5th edn, Pearson Education.

Lerman, S. (1977), 'Location, housing, automobile ownership, and the mode to work: A joint choice model', *Transportation Research Board Record* **610**, 6–11.

McFadden, D. (1974), Conditional logit analysis of qualitative choice behavior, *in* P. Zarembka, ed., 'Frontiers in Econometrics', Academic Press, New York, pp. 105–142.

McFadden, D. (1978), Modeling the choice of residential location, *in* A. Karlqvist, L. Lundqvist, F. Snickars & J. Wiebull, eds, 'Spatial Interaction Theory and Planning Models', North Holland, Amsterdam, pp. 75–96.

McFadden, D. (1981), Econometric models of probabilistic choice, *in* C. Manski & D. McFadden, eds, 'Structural Analysis of Discrete Data with Econometric Applications', MIT Press, Cambridge, MA, pp. 198–272.

Quigley, J. (1976), 'Housing demand in the short-run: An analysis of polytomous choice', *Explorations in Economic Research* **3**, 76–102.

Train, K. E. (2003), *Discrete Choice Methods with Simulation*, Cambridge University Press.

Waddell, P. (2002), 'UrbanSim: Modeling urban development for land use, transportation, and environmental planning', *Journal of the American Planning Association* **68**(3), 297–314.

Waddell, P. (2011), 'Integrated land use and transportation planning and modeling: Addressing challenges in research and practice', *Transport Reviews* **31**(2), 209–229.

Waddell, P., Ulfarsson, G., Franklin, J. & Lobb, J. (2007), 'Incorporating land use in metropolitan transportation planning', *Transportation Research Part A: Policy and Practice* **41**, 382–410.

Waddell, P., Wang, L. & Liu, X. (2008), UrbanSim: An evolving planning support system for evolving communities, *in* R. Brail, ed., 'Planning Support Systems for Cities and Regions', Cambridge, MA: Lincoln Institute for Land Policy, pp. 103–138.

Wang, L. & Waddell, P. (2013), A disaggregated real estate demand model with price formation for integrated land use and transportation modeling, *in* 'The 92th Annual Meeting of the Transportation Research Board'.